Journal of Transport Economics and Policy, Volume 53, Part 2, April 2019, pp. 150–174

The Total Size of an Airline and Flight Delays

Joep van Montfort and Vincent A. C. van den Berg

Address for correspondence: Vincent A. C. van den Berg, Vrije Universiteit Amsterdam, de Boelelaan 1105, 1081HV Amsterdam, the Netherlands (v.a.c.vanden.berg@vu.nl).

We are thankful for the comments of the anonymous reviewer, editor, and Mark Lijesen. Any remaining errors are ours. This research does not necessarily represent the views of our employers.

Abstract

We examine the relationship between the total size of an airline and its flight delays. Total size is measured by its total market share, total amount of assets, or total number of full-time equivalent employees. In our estimations, important controls are the degree of competition on the route and airport. We also add numerous other controls and route-specific fixed effects. We find that the larger an airline is nationwide, the smaller its average delay time and delay or cancellation occurrence. An origin airport with less competition may lead to more delays. A less competitive route may reduce delays.

Final version: January 2019

1.0 Introduction

In 2016, more than 17 per cent of the commercial flights in the USA were delayed by at least 15 minutes (see Section 3). Delays are the most common sources of complaints from airline passengers (Dresner and Xu, 1995). There are several explanations for these delays. Airlines argue that it is not their fault; they mention extreme weather and bad air traffic control as causes. Policy makers argue that there are other reasons: airlines overschedule and make use of too-small aeroplanes that need the same airport resources as large ones but take fewer passengers. Airlines may ignore the high external cost of scheduling planes, and hence may use too-small planes with high external costs per passenger (Ball *et al*., 2010). Moreover, the incentives to reduce the number of delays may be too low on non-competitive routes and airports (Mazzeo, 2003). The costs of delays are enormous. For example, Ball *et al*. (2010) estimated that the yearly total costs of delays for the USA were $32 billion.[1]

The degree of airline competition on airports and flight routes has decreased in recent decades. On average, there are now only two carriers on a route (Rupp *et al*., 2006). American, Southwest, and Delta airlines are the three largest airlines in the USA. Together, they had a market share of over 50 per cent of the domestic airline market in 2016 (see Section 3). The government and consumer organisations have expressed concerns over the effects of these market concentrations and the increase in delays (Mazzeo, 2003).

Daniel (1995), Mayer and Sinai (2003), Mazzeo (2003), Rupp *et al*. (2006), Ater (2012), and Greenfield (2014), among others, studied the relationship between flight delays and the level of competition on a *route* or at the *airport*, thereby testing theories about the effect of competition on service quality.

For competition *on the route*, the results are mixed. Most authors find that more competition shortens delays (Mazzeo, 2003; Greenfield, 2014; Cao *et al*., 2017), but Rupp *et al*. (2006) find that more competition leads to longer delays.

For competition at the airport level, there may also be opposing effects on delays. Competition may force airlines to offer a higher-quality service and thus shorter delays. However, following, for instance, Brueckner (2002), and Pels and Verhoef (2004), an airline with a large share of the flights at an airport may internalise the congestion it imposes on itself. If congestion causes more delays, this impacts on all the airline's existing flights, and this lower quality reduces what its customers are willing to pay in fares. If so, then more competition would result in more delays, However, the empirical results on this hypothesis are mixed, with some authors finding support (Mayer and Sinai, 2003; Ater, 2012), and others not (Daniel, 1995; Daniel and Harback, 2008; Rupp, 2009). We do not expect nationwide size to affect internalisation — all else being equal at the airport — but, of course, larger airlines also tend to be large players at many airports.[2]

Previous research used the airline's market share on the route or airport for the independent variable of interest. Our innovation is that we consider the effect of the *total size* of an

[1] Half of these costs were borne by the consumer due to time lost, cancellations, and missed connections. Due to these costs, customers are also flying less often than they otherwise would, which negatively affects airlines and airports.

[2] If you are a large airline, but have one flight per week at a particular airport, then there are no other own flights to impose congestion on there.

airline on delays, while also controlling for the degree of competition on the route and at the airport. This allows us to separate the effects of competition from the effect of overall size. Previous studies only looked at competition, even though their measures for competition are correlated with airline size. We expect to find opposing effects. On the one hand, a larger total size may reduce competition, resulting in an inferior service quality. On the other hand, a larger total size may improve the operational management and planning, potentially reducing delays. Moreover, a delayed flight is a bad signal for customers, so a larger airline may need to invest more in quality to protect its brand. It is not clear which effects will dominate.

This paper analyses 4.8 million individual flights within the USA in 2016, using linear regression models. We use two measures of delays as dependent variables: delay time in minutes; and whether or not a flight arrives more than 15 minutes later than scheduled. Both delay measures have been heavily used in the literature. We also look at cancellations as an alternative dependent variable. Independent variables include total airline size, route market structure, airport market structure, distance, and characteristics of the aeroplane, flight, and airport. We measure the total size of an airline by the total market share, the total amount of assets, or the total number of full-time equivalent employees (FTEs). We add fixed effects for the combination of origin and destination airport to allow for route-level and airport-level idiosyncrasies. We also add fixed effects for the month, day of the week, and time of day. Including airline fixed effects is impossible, as total airline size hardly varies over the year. Finally, we control for 'extreme weather'[3] by subtracting delays due to such weather from the delay time. This results in sharper estimates without affecting point estimates significantly.

The remainder of the paper is structured as follows. Section 2 gives an in-depth discussion of the literature. Sections 3 and 4 describe the data and empirical set-up. Section 5 discusses the main regressions and numerous sensitivity analyses. Section 6 concludes.

2.0 Literature Framework

2.1 Dimensions of airline quality

Service quality of an airline is one of the most important criteria for customers in choosing an airline (Truitt and Haynes, 1994). Gursoy *et al*. (2005), and Chen and Gayle (2019), argue that timeliness is an important attribute to quality. Chen and Gayle (2018) define timeliness in three dimensions. The first dimension is '*On-time performance*', which is measured by delay time in minutes. The second dimension is '*Schedule delay*', which is the gap between a passenger's preferred departure time and actual departure time. The third dimension is '*Total travel time*', which is the time it takes a passenger to travel from the origin airport to the destination airport.

In the widely used 'Airline Quality Rating' from Bowen and Headley (2001), on-time performance is one of the criteria for airline quality. Moreover, other factors that are affected by delays are part of this rating — for instance, customer complaints, and lost baggage. Mazzeo (2003), Mayer and Sinai (2003), Rupp *et al*. (2006), Greenfield (2014), and Yimga (2016) all use dimensions of timeliness as measurements of quality.

[3]As defined by the US Department of Transportation; see Section 3 for details.

2.2 On-time performance

The US Department of Transportation defines a flight as delayed if it arrives more than 15 minutes later than scheduled in the Computerized Reservations Systems.[4] Brueckner (2002), for instance, uses this definition. An advantage of this measure is its simplicity. Consumers like to arrive on schedule, and hence carriers use this measurement to increase their service quality. A disadvantage is that carriers may pad their flight schedule to lower delays on paper (Mazzeo, 2003). Therefore, Mayer and Sinai (2003) created their own dependent variable, 'excess travel time'; this is the difference between actual travel time of a flight and the minimum travel time on the route. With this approach, they estimated the efficiency of a flight. Rupp *et al*. (2006) used the monthly percentage of flights arriving within 15 minutes of schedule and the monthly average minutes late.

Bad weather causes and increases delays. In our data set, extreme weather — as defined by the US DOT category — directly caused 0.51 per cent of the delayed flights and 4.35 per cent of the total delay time. The National Aviation Systems (NAS) caused 22.9 per cent of total delay time. The NAS includes a broad set of conditions such as non-extreme weather, airport operations, heavy traffic, and air traffic control.[5] Non-extreme weather slows down the flight, but does not prevent flying. On average, 31.7 per cent of the NAS delays were caused by weather. For example, Mayer and Sinai (2003), Mazzeo (2003), Rupp *et al*. (2006), and Greenfield (2014) considered weather delays, again indicating the importance of taking weather into account.

Congestion has been a large problem for airlines for a long time. It can be airport-specific due to, for instance, too short or too few runways (Craig, 1988), but it also varies over the hours of a day (Mayer and Sinai, 2003). This is partly because demand varies over the day (Borenstein and Netz, 1999), and partly because delays build up over time. The frequency of flights differs during the year. Holiday periods and national holidays can explain that certain routes are busier than others during certain months. Hence, congestion also varies over the months. The frequency of flying also differs over the days. Mazzeo (2003) confirms this. He also argued and empirically found that delays are affected by the type and age of the aircraft used.

A hub airport is an airport where passengers can connect with other flights. Rupp (2009) argues that on-time performance is better at hub airports. Passengers need to catch their connecting flights, leading to high costs in the case of delays. Hence, airlines try to bring down their delays in operating flights from and to their hub airports (Morrison and Winston, 2007). Conversely, a hub airport also needs arriving and departing flights that are close together in time, increasing congestion, and meaning that delays multiply quickly. Hence, an airline having a hub airport may also impose extra delays on its own and other airline's flights (Mayer and Sinai, 2003).

So, delays can be caused by bad weather, hubbing, congestion, or variations in demand over the months or days, and the age and type of aircraft used. However, they may also be caused by too much or too little competition.

---

[4]Source: www.rita.dot.gov/bts/help_with_data/aviation/index.html (accessed on 28 July 2017).
[5]Source: www.transtats.bts.gov/OT_Delay/ot_delaycause1.asp?display = data&pn = 1 (accessed on 23 August 2017).

2.3 Competition and quality: previous research

This section will describe the previous research on the connection between competition and service quality.

2.3.1 Competition at the airport

More competition may force airlines to set a higher quality. However, following Daniel (1995), Brueckner (2002), and Pels and Verhoef (2004), a larger airline may internalise more of the congestion it imposes on itself. Hence, it considers that causing more congestion delays all its existing flights, and this lowers the amount that its customers are willing to pay in fares. If so, more competition implies less internalisation and therefore more delays. However, following Daniel (1995) and Silva *et al*. (2014), potential entry may make such internalisation impossible. The empirical literature also has mixed results on this internalisation hypothesis. Daniel (1995), and Daniel and Harback (2008), conclude that for most hubs in the USA, potential entry by a competitive fringe indeed prevents internalisation. The empirical findings of Brueckner (2002), as well as those of Mayer and Sinai (2003), show limited support for internalisation, and Rupp (2009) has no empirical support for the internalisation hypothesis. Conversely, Ater (2012), using a different empirical modelling technique, does find support for internalisation.

Mazzeo (2003) investigated the effect of competition on service quality in the US airline industry. To determine the degree of competition, he used the market share of an airline at an airport. The data are from the US Department of Transportation. It has 800,000 individual flights, including all flights scheduled between the 50 major airports in 2000. These airports were selected to include all of the major airline hubs, but also a few airports in smaller cities.

Mazzeo (2003) evaluates the on-time performance as a function of different variables. The most important are on concentration effects.[6] These variables are the *airport market share*, whether there is only one airline on a route, and the *route* HHI (Herfindahl-Hirschman Index) considering both direct trips and indirect trips via a hubbing airport. Dependent variables were ‘Minutes Late’ and if a flight is more than 15 minutes late. Mazzeo concludes that airlines use their market power *at the airport* and *on the route* to impose lower quality through increased delays.

Mayer and Sinai (2003) use excess travel time — the difference between actual travel time and the minimum travel time on the route — as their delay measure. They considered all US domestic flights and use monthly data from 1988 until 2000. They argue that using hubbing to increase the number of connections to other airports creates new markets, and thereby benefits airlines and consumers. Delays could just be the counterpart of these benefits, as every hubbing flight creates congestion. Mayer and Sinai empirically find that congestion increases with hubbing activity and decreases with market concentration. Hub carriers cluster their flights in short time spans, making it possible for their passengers to use many connections. In comparison, non-hub flights — operating at the same airport — fly with less delay time.

[6]Other controls include variables about the weather, and variables about flight, airport, and aeroplane characteristics. These variables also controlled for congestion on airports, which varies over the hours of a day (Mayer and Sinai, 2003). Mazzeo (2003) argues that there may be strategic deployment of certain types of aircrafts and age of the aircrafts. This would influence delays, and therefore he takes the type and age of an aircraft into account.

2.3.2 Competition on the route

For competition at the route level, we do not expect any internalisation. Similarly, a larger nationwide size does not seem likely to lead to more internalisation as long as the airport shares stay the same.

However, there may very well be effects from direct competition on quality. For instance, more route competition may force airlines to set a higher quality, and thus have fewer and shorter delays — if they want to attract customers. As Chen and Gayle (2018) argue for routing quality, on highly competitive routes, profits are low, and airlines may care less about attracting more customers and more about keeping costs low. If so, then on competitive routes, even more competition would lead to a lower quality.[7]

Mazzeo (2003) and Cao *et al*. (2017) empirically find that delays increase if the HHI on a route is higher; therefore, more competition on the route leads to shorter delays. Cao *et al*. (2017) also conclude that the effect is non-linear. The effect is stronger for competitive settings, while for markets that already have little competition, the effect of further decreased competition is small. Similarly, Gil and Kim (2016) conclude that entry of a low-cost carrier, and thus more competition, induces the incumbent to have fewer delays and cancellations.

Greenfield (2014) analysed delay occurrence as a function of route market structure, airport traffic, weather, and exogenous demand and cost shifters. In contrast with previous research, market structure is an endogenous variable. He argues that ignoring this leads to endogeneity bias. For instruments for the market structure, he used the lagged market structure and airline mergers. He finds that less competition means longer delays. Moreover, the effect is three times stronger when treating the market structure as endogenous. He argues that this shows the importance of determining the market structure endogenously.

Conversely, Rupp *et al*. (2006) find that less competition leads to shorter and less frequent delays.[8] They use several measurements of competition on the routes: number of carriers; effective competitors; route market share; and a monopoly route indicator. The effects seem similar in all their set-ups: competitive routes have slightly lower on-time arrival percentages (between 0.2 and 0.8 percentage points) and longer average delays (between 0.3 and 0.7 minutes).

The results in the literature on the effect of route competition are mixed, although most find that more competition leads to a higher quality by reducing delay. Similarly, for competition at the airport, results are also mixed, but most authors find that more competition at the airport increases delays.

2.3.3 Mergers and alliances

Yimga (2016) investigated the relationship between alliances and on-time performance. He finds evidence that codeshare agreements improve the on-time performance rate and allow for more efficient connections between flights. The net effects depend on the pre-agreement situation on routes.

[7] Gal-Or (1983) theoretically showed that more competition may lower quality when competition does not affect the cost structure.

[8] Rupp *et al*. (2006) investigate how route competition affects arrival delay time. They have a large data set with 27,000 monthly observations along 150 routes from 1997 to 2000.

Forbes and Lederman (2010) studied owned versus contracted regional airlines that act as feeders for the main airline. They find that an owned regional airline at an airport results in fewer delays and cancellations. They argue that this stems from the benefit that integration allows for better coordination.

Steven *et al*. (2016) considered airline mergers, finding that mergers directly increase the frequency of delays but lower the occurrence of cancellations. However, there is also the indirect effect that mergers increase route concentration (as measured by the HHI), and this indirectly lowers the quality. Accordingly, this results in even more frequent delays and a net increase in the average cancellation rate when we also consider the indirect secondary effect.

Prince and Simon (2017) investigated the effect of five mergers on the on-time performance of the merged airlines. In the short run, they found a small decrease in on-time performance and thus quality; however, in the long run, the on-time performance increases, which they argue is caused by efficiency gains from being larger.

Rupp and Tan (2018) studied the effect of four mergers via the de-hubbing they cause, in that some airports will no longer be hubs. They found that the de-hubbed airport sees fewer flights, which lowers the quality as customers have less choice regarding when to travel. However, the fewer flights also imply less congestion, delays, and cancellations, and this raises the service quality on these dimensions of the merged airlines and the other airlines.

3.0 Data

We use several data sets, which are from the US Department of Transport. The first is the Airline On-Time Performance data set for 2016.[9] It contains over 5.6 million flights for the 12 airlines that had to report delay data. For 0.8 million flights, there is some information missing. Consequently, the final data set has 4.8 million observations. Our second source is the B-43 Inventory data set of the US DOT. It is on aeroplane characteristics such as age and size. Finally, we used two financial data sets, schedule P-1(a) and schedule B-1,[10] for information on the total amount of assets and number of full-time equivalent employees (FTEs).[11]

For the size of an airline, we use three measurements: (1) MARKET_SHARE is its total number of domestic flights as a percentage of all US domestic flights; (2) TOTAL_ASSETS is its assets in billions of dollars; and (3) TOTAL_FTE is its total number of full-time equivalent employees (FTEs), normalised to be expressed in 10,000 employees. We use two distinct measurements of delays. The first follows Chen and Gayle (2018), and is the minutes that a flight arrives delayed compared to its schedule. If a flight is on time or arrives earlier than scheduled, the delay is zero as this is a good performance. For the second

[9]Source: www.transtats.bts.gov/Tables.asp?DB_ID = 120&DB_Name = Airline%20On-Time%20Performance%20Data&DB_Short_Name = On-Time (accessed on 28 July 2017).

[10]Source: www.transtats.bts.gov/dataindex.asp?index = S&listorder = TABLES (accessed on 28 July 2017).

[11]StataSE 14 was used for the calculations and regressions. The coding for calculations and estimations is available on request. The data can be found via the supplied URLs.

Table 1
Airline and Its Market Share, Per Cent Flights Delayed More Than 15 Minutes, and Average Delay

Airline	*Market share (% of total)*	*Delayed flights (% of total)*	*Average delay (minutes, corrected for weather)*
Southwest Airlines	25.97	18.05	9.90
Delta Airlines	18.08	13.07	9.25
American Airlines	7.30	16.41	11.91
SkyWest Airlines	11.35	17.27	12.04
United Airlines	10.98	17.95	13.88
ExpressJet Airlines	10.08	17.93	10.92
JetBlue Airlines	5.48	23.69	15.79
Alaska Airlines	3.38	11.93	6.63
Spirit Airlines	2.62	24.56	16.59
Frontier Airlines	1.76	22.58	16.63
Hawaiian Airlines	1.57	8.64	4.80
Virgin America	1.42	22.82	13.73
All	100.00	17.12	11.19

dependent variable, we follow the Department of Transportation: a delay occurs if a flight arrives more than 15 minutes later than scheduled.

Table 1 shows that market share varies substantially between the 12 airlines, and the same holds for the percentage of flights delayed more than 15 minutes. The mean arrival delay is 11.65 minutes, or 11.19 if we ignore delays caused by weather. Moreover, 17.12 per cent of the flights are late by 15 minutes or more.

To investigate accurately the effect of the total market share on delays, we need to control for other factors in the categories: airport and market structure, weather, congestion, date, and characteristics of the airport, flight, and aeroplane. All used variables are defined and summarised in Table A.1 in the Appendix. We will discuss the choice of these variables hereafter.

We aim to disentangle the effect of the total airline size from the competition at the route and airport level. The first variable for this is HHI_ORIGIN. It equals the Herfindahl-Hirschman Index (HHI), based on the flights departing from an origin airport o in month m:

$$HHI\_ORIGIN_{om} = \sum_{j=1}^{j=N_{om}} (flight\_share_{jom})^2.$$

Here, N_{om} is the number of airlines flying from airport o, and $flight\_share_{jom}$ is airline j's share of flights departing from o in month m. The second variable HHI_DESTINATION is similarly defined using the flights arriving at the destination airport. Finally, SHARE_OD is the airline's share of flights in a month between the origin and destination (OD) airports. It does not consider indirect hubbing connections, as the data are on individual flights and not on passenger itineraries.[12]

[12] Including the HHI for the OD pair proved impossible due to the OD pair-specific fixed effects. Including both the airline's share at an airport and the airport's HHI also did not work, due to collinearity issues.

Weather has a large effect on delays. The data set contains information on minutes delay due to extreme weather if the delay exceeds 15 minutes. Therefore, extreme weather delay in minutes will be subtracted from the arrival delay in minutes to obtain a corrected delay measure. For delays under 15 minutes, there is no information on extreme weather delays. To prevent missing observations for 99.49 per cent of the data set, we set the weather delay to zero for these observations, as extreme weather should cause long delays, and indeed the average extreme weather delay is about 50 minutes. As we will see in our sensitivity analyses, this subtraction of extreme weather delays has little to no effect on the coefficient of overall airline size, but it does reduce the standard error noticeably.

We will also control for the capacity of the plane used and its age. An older aeroplane may have a higher chance of technical problems. The size of an aeroplane may also alter its congestion effect and how it is affected by congestion. It seems very likely that, per passenger, a larger plane causes less congestion, but per plane it may impose more; this is similar to how one bus imposes more congestion than one car, but per passenger, the bus imposes less congestion. We should allow for these possible effects.[13]

To allow for differences in delays over months, days of the week, and time of day, we include dummies on these. By using dummies, we allow for non-linear effects of time that may also fluctuate. For instance, if there is more air travel in the summer and December, it is difficult to control for this using a linear or quadratic effect.

A hub is used by the Federal Aviation Administration to identify busy airports. An airport is a medium hub if it has between 0.25 per cent and 1 per cent of total US enplanements. A large hub has more than 1 per cent of this total. Table 2 summarises the hubs.[14] We allow for delays being different according to whether an airport is a medium or large hub via four airport-specific dummies: MEDIUM_HUB_ORIGIN, LARGE_HUB_ORIGIN, MEDIUM_HUB_ DEST, and LARGE_HUB_DEST. We also allow for delays being different if the flight is to or from an airline-specific hub via the airline and airport specific dummies: OUT_HUB_AIRPORT and IN_HUB_AIRPORT. Airlines may internalise more congestion at their own hubs as delays spread, as passengers are delayed for their follow-up flights. Conversely, a hub airport has many flights arriving and departing close together in time, implying more congestion for the same number of flights. These hub dummies allow for hub-related congestion. We also allow for congestion directly via the variables DEPARTURES_ORIGIN and ARRIVALS_DEST. The latter, for example, gives the monthly arriving flights at the destination.

We add fixed effects for the combination of origin and destination airport. These control for airport capacity and other airport-specific factors that cannot be measured

[13]To do so, we link the aeroplane used with the plane characteristic B-43 data set. For aeroplane size, we use weight in pounds. Using seat capacity may have allowed studying effects from congestion internalisation, traffic density, and flight connections. Nevertheless, size in pounds may be more related to how much congestion a plane imposes on the runway and the terminal (where delays at the terminal also affect arrival delay).

[14]www.faa.gov/airports/planning_capacity/passenger_allcargo_stats/passenger/media/cy15-commercial-service-enplanements.pdf (accessed on 28 July 2017).

Table 2
Airlines and Their Hub Airports

Airline	*Hub airports*
Southwest Airlines	Phoenix, Los Angeles, San Francisco, Denver, Orlando, Atlanta, Chicago, Baltimore-Washington, and Las Vegas
Delta Airlines	Los Angeles, Atlanta, O'Hare, Northern-Kentucky, Boston, Detroit, Minneapolis, New York (LaGuardia and John F. Kennedy), Portland, Memphis, Dallas-Fort Worth, Salt Lake City, and Seattle
American Airlines	Phoenix, Los Angeles, Miami, O'Hare, Lambert-St Louis, New York, Charlotte-Douglas, Raleigh Durham, Philadelphia, Nashville, Dallas-Fort Worth, and Ronald Reagan Washington
SkyWest Airlines	O'Hare, Seattle, Portland, Los Angeles, San Francisco, Detroit, Minneapolis, Denver, George Bush, and Phoenix
United Airlines	Los Angeles, Detroit, Denver, O'Hare, Newark Liberty, Cleveland, Pittsburgh, George Bush, and Washington Dulles
ExpressJet Airlines	Cleveland Hopkins, George Bush, Newark Liberty, O'Hare, and Seattle
JetBlue Airlines	Ft Lauderdale-Hollywood, Boston, and Miami
Alaska Airlines	Ted Stevens Anchorage, Los Angeles, Portland, and Seattle-Tacoma
Spirit Airlines	Ft Lauderdale-Hollywood, O'Hare, and Detroit
Frontier Airlines	Denver, O'Hare, Northern-Kentucky, Kansas, Trenton, Cleveland, and General Mitchell
Hawaiian Airlines	Honolulu and Kahului
Virgin America	Los Angeles and San Francisco

directly. They also allow for route-specific effects and may prevent possible bias from reverse causality.[15]

4.0 Models and Hypotheses

To predict the effect of the size of an airline on delays, several regressions will be used. An airline that is larger nationally may have more resources, be more efficient due to economies of scale, and internalise more congestion. All this would tend to make the airline invest more in limiting delays and thus increase quality. However, it may also face limited competition, lessening the need to invest in fewer and shorter delays. Nevertheless, we expect the first effects to dominate, and thus delays are shorter and less frequent for larger airlines. We also control for market structure at the airport and route structure. Here, we expect that routes with less competition will have longer and more frequent delays, as there is less competitive pressure. For the degree of competition at the airport, there is also the opposing force that less competition may lead to more internalisation of congestion imposed on own flights.

[15] For instance, an airline can fly between small airports with little congestion, which means few delays, and faster boarding and security checks. This in turn may increase popularity and thereby the market share. Yet a larger airline might also fly between high-demand cities with congested airports. Without fixed effects, the market share variable could measure all effects: the effect of the airline size, and the effects of congestion or other airport-specific factors.

The first regression has as the dependent variable ARR_DELAY_CORR, which equals ARR_DELAY (=arrival delay time) minus WEATHER_DELAY, which is the delay time caused by extreme weather following the US DOT data set:[16]

$$\begin{aligned} ARR\_DELAY\_CORR_i = {} & \beta_0 + \beta_1\, MARKET\_SHARE_i + \beta_2\, HHI\_ORIGIN_i \\ & + \beta_3\, HHI\_DESTINATION_i + \beta_4\, SHARE\_OD_i \\ & + \beta_5\, DEPARTURES\_ORIGIN_i + \beta_6\, ARRIVALS\_DEST_i \\ & + \beta_7\, OUT\_HUB\_AIRPORT_i + \beta_8\, IN\_HUB\_AIRPORT_i \\ & + \beta_9\, AIRPLANE\_AGE_i + \beta_{10}\, AIRLINE\_CAPACITY_i \\ & + \beta_{11}\, MEDIUM\_HUB\_ORIGIN_i + \beta_{12}\, LARGE\_HUB\_ORIGIN_i \\ & + \beta_{13}\, MEDIUM\_HUB\_DEST_i + \beta_{14}\, LARGE\_HUB\_DEST_i \\ & + \beta_{15}\, DISTANCE_i + \boldsymbol{\gamma_1\, MONTH} + \boldsymbol{\gamma_2\, DAY\_OF\_WEEK_i} \\ & + \boldsymbol{\gamma_3\, DEP\_TIME_i} + \varepsilon_i. \end{aligned} \tag{1}$$

The variables MONTH, DAY_OF_WEEK, and DEP_TIME are in bold vector notation, and are vectors of dummies that control for time effects.

There are some airport- and route-specific factors that are not considered in equation (1), such as airport capacity and demand for travel between two airports. Equation (2) considers these by using a fixed effect on the combination of origin and destination airports. Hence, flights from Chicago O'Hare to Atlanta get a different fixed effect than those flying from Chicago to San Francisco. In total, there will be 4,492 fixed effects for the OD pairs:

$$\begin{aligned} ARR\_DELAY\_CORR_i = {} & \beta_0 + \beta_1\, MARKET\_SHARE_i + \beta_2\, HHI\_ORIGIN_i \\ & + \beta_3\, HHI\_DESTINATION_i + \beta_4\, SHARE\_OD_i \\ & + \beta_5\, DEPARTURES\_ORIGIN_i + \beta_6\, ARRIVALS\_DEST_i \\ & + \beta_7\, OUT\_HUB\_AIRPORT_i + \beta_8\, IN\_HUB\_AIRPORT_i \\ & + \beta_9\, AIRPLANE\_AGE_i + \beta_{10}\, AIRLINE\_CAPACITY_i \\ & + \boldsymbol{\gamma_1\, MONTH} + \boldsymbol{\gamma_2\, DAY\_OF\_WEEK_i} + \boldsymbol{\gamma_3\, DEP\_TIME_i} \\ & + FE\_OD_i \varepsilon_i. \end{aligned} \tag{2}$$

The distance is constant between OD pairs and the four airport-specific hub dummies are constant for an airport. Accordingly, in our fixed-effects estimations, these variables cannot be included and are controlled for by the fixed effects. We do not include airline fixed effects as total airline size hardly varies over the year, so it would drop out if we included fixed effects for the airlines, and total airline size is the independent variable of main interest.

Our second dependent variable is the dummy ARR_DELAY15, which is one if the flight arrives 15 minutes later than scheduled, and otherwise it is zero. A linear probability

[16]Mayer and Sinai (2003) argue that airlines may pad their schedule to have shorter delay on paper. In the sensitivity analysis, we will also look at this by using their measure of 'excess travel time', which is compared to the quickest time on a route. This shortest travel time is almost always well below the scheduled time.

model will be estimated based on equation (2):[17]

$$\begin{aligned}ARR\_DELAY15_i = {} & \beta_0 + \beta_1\, MARKET\_SHARE_i + \beta_2\, HHI\_ORIGIN_i \\ & + \beta_3\, HHI\_DESTINATION_i + \beta_4\, SHARE\_OD_i \\ & + \beta_5\, DEPARTURES\_ORIGIN_i + \beta_6\, ARRIVALS\_DEST_i \\ & + \beta_7\, OUT\_HUB\_AIRPORT_i + \beta_8\, IN\_HUB\_AIRPORT_i \\ & + \beta_9\, AIRPLANE\_AGE_i + \beta_{10}\, AIRLINE\_CAPACITY_i \\ & + \boldsymbol{\gamma_1\, MONTH + \gamma_2\, DAY\_OF\_WEEK_i + \gamma_3\, DEP\_TIME_i} \\ & + FE\_OD_i \varepsilon_i. \end{aligned} \tag{3}$$

We will also use two other measurements of airline size as independent variables. So instead, we will also estimate equations (1)–(3) with TOTAL_ASSETS (total value of assets in billions of dollars) instead of MARKET_SHARE and with TOTAL_FTE (total full-time employee equivalent).

5.0 Empirical Analysis

5.1 Results

This section summarises the findings from the different models with the dependent variables ARR_DELAY_CORR and ARR_DELAY15. Table 3 shows the results when MARKET_SHARE measures the airline's total size. The standard errors were clustered on the combination of origin and destination airport, allowing for heteroscedasticity of the errors and serial correlation in the errors. Columns 2 and 3 also allow for 4,492 fixed effects on the OD pair airports, but it seems prudent to allow for possible remaining serial correlation.

In column 1, which does not allow for fixed effects, there are strange results. For instance, it suggests that more departing flights lead to shorter delays. This indicates that not allowing for fixed effects leads to inconsistent estimates, and a Hausman test supports this. Therefore, we focus on the fixed-effect estimations.

In columns (2) and (3), we see that a larger nationwide market share of flights significantly lowers the delays in minutes and the chance of having a delay of more than 15 minutes (which is indicated by $ARR\_DELAY15 = 1$ instead of 0). A share that is one percentage point higher leads to 0.12 minutes lower delay. This is even though we allow for the market structure at the airports and routes.

A larger HHI at the origin airport — and thus less competition — leads to longer delays and a higher chance of a delay. For the HHI at the destination airport, the coefficient is not significant, and the sign differs between columns (2) and (3). This seems to contradict the

[17]Perhaps a probit or logit model would be more appropriate as it ensures that the probabilities are between zero and one, but our computational resources were not good enough to run such non-linear models with such a large data set. Moreover, the coefficients of probits or logits are hard to interpret. Our linear probability model (3) is directly comparable to specification (2), and it offers unbiased estimates of the mean marginal effects. Our errors may be non-normal, leading to issues with the standard errors.

Table 3
Main Estimations of the Effect of Total Airline Size and Market Structure on Delays

	(1) ARR_DELAY_CORR		(2) ARR_DELAY_CORR		(3) ARR_DELAY15	
	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat
MARKET_SHARE	−0.14***	−8.50	−0.12***	−8.37	−5.18E-04**	−2.38
HHI_ORIGIN	−1.15*	−2.90	5.64**	3.37	4.77E-02**	2.46
HHI_DESTINATION	−2.46***	−6.46	0.93	0.77	−3.92E-03	−0.28
SHARE_OD	−0.01***	−3.49	−0.03***	−8.85	−4.57E-04***	−8.45
DEPARTURES_ORIGIN	−2.88E-05*	−2.01	2.03E-04***	3.49	2.28E-06**	3.31
ARRIVALS_DEST	1.05E-05	0.71	1.45E-04**	2.53	2.04E-06**	2.72
DISTANCE	−0.35**	−2.18				
AEROPLANE_CAPACITY	7.25E-06***	3.70	4.11E-06	1.85	−3.62E-08	−1.18
AEROPLANE_AGE	7.39E-02***	9.33	1.17E-01***	20.82	1.16E-03***	14.54
OUT_HUB_AIRLINE	−1.05***	−4.03	−0.39	−1.45	−1.44E-02***	−3.79
IN_HUB_AIRLINE	−1.47***	−5.67	−1.31***	−4.96	−7.58E-03**	−2.00
MEDIUM_HUB_ORIGIN	−0.80**	−2.55				
MEDIUM_HUB_DEST	0.51	1.74				
LARGE_HUB_ORIGIN	0.34	0.97				
LARGE_HUB_DEST	1.98***	5.70				
MONTH dummies	YES		YES		YES	
DEP_TIME dummies	YES		YES		YES	
DAYS_OF_WEEK dummies	YES		YES		YES	
Fixed effects on the OD pair	NO		4,492		4,492	
Observations	4,798,318		4,798,318		4,798,318	
R-squared	0.029		0.028		0.042	

Notes: Significance levels are indicated: * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$. All standard errors were clustered on the combination of origin and destination airport. For the panel regressions with fixed effects on OD pair, the R-squared is the within R^2 of the part of the variance of the demeaned data that is explained by the model. Coefficients of the dummies for DEP_TIME, DAYS_OF_WEEK, and MONTH are available on request.

results in Mayer and Sinai (2003), and Ater (2012), who found that less competition leads to shorter delays, due to internalisation of congestion by larger airlines. However, Daniel (1995), and Daniel and Harback (2008), using a different empirical set-up, found that large hub airlines cannot internalise congestion due to the potential entry of a competitive fringe.[18]

A higher SHARE_OD means that the airline has a higher share of flights in a month between an origin and destination airport. Contrary to our expectations, a higher route share leads to a shorter delay and a lower chance of delays, suggesting that *less* competition

[18] If we redo the estimation without the total market share variable, the results for the other variables stay quantitatively the same; this is true even when we also include airline fixed effects. In addition, using only origin airport fixed effects instead of OD pair fixed effects means that results remain quantitatively unchanged.

on a route leads to *shorter* and *fewer* delays. As Chen and Gayle (2018) argue for routing quality, more competition may force airlines to offer more quality *if they want* to attract customers, but they find that, on highly competitive routes, even more competition lowers quality. The intuitive reason is that, with very high competition, profits are always low; therefore, it may not be worthwhile to invest in quality to attract more customers, and it may be more profitable to reduce costs by reducing the quality.

We included numerous controls. The coefficients of the monthly congestion variables DEPARTURES_ORIGIN and ARRIVALS_DEST show that in months with more aircraft movements, an individual flight has a longer expected delay and a higher chance of a delay exceeding 15 minutes. If the origin or destination airport is an airline-specific hub, the arrival delay time of its own flights will decrease compared to flights of airlines that do not use this airport as a hub. This suggests that airlines may consider that the congestion they cause at hubs also delays their other hubbing flights, as was argued by Rupp (2009). In line with Pai (2010), a larger or older plane significantly increases delays.

5.2 Sensitivity analyses

Now we investigate the sensitivity of our results to changes in the regression equation or variables. Tables A.2 and A.3, in the Appendix, use TOTAL_FTE and TOTAL_ASSETS as alternative measures for total airline size. They show that arrival delay time decreases significantly with the total amount of assets in billions of US dollars and with the total employment. Thus, the effect of total airline size seems robust to the way of measuring this size.

A large percentage of flights has a zero delay or a negative delay that we set to zero. This may affect our results and could imply that standard fixed-effect regressions are not appropriate. To test this, we redo the analysis of equation (2) in column 1 of Table A.4 for only the 1.6 million observations with a *positive delay*. This results in stronger effects of the nationwide market share, as well as of the airport HHI and route share variables. The standard errors of these coefficients are also smaller.

Column (2) of Table A.4 redoes the estimation of equation (2), but now *without subtracting the weather delays*. This is measured by the variable ARR_DELAY. For column (3), we drop the observations with a zero delay under this alternative delay measure. Only 0.51 per cent of flights saw extreme weather, so we expect limited changes. The coefficients of interest only change slightly, but the standard errors increase. The exception is SHARE_OD, whose coefficient becomes much larger, suggesting an outlier issue. This indicates that our correction for weather did not affect point estimates meaningfully, but did sharpen them.

The literature often uses *logs of the dependent and independent variables*. The advantages of using logs include that it reduces the effects of outliers and that the parameters can be interpreted as elasticities. Estimating the model of equation (2) using a log-log specification does not alter the results substantially. In column 1 of Table A.5, we use the log of ARR_DELAY_CORR. The number of observations drops, as the delay is often zero and the log of zero does not exist. Therefore, in column (2) we use the log of (ARR_DELAY_CORR + 1) instead. Finally, column (3) uses the log of the delays without the weather delays subtracted. The effect of the airline size stays similar in all these specifications: a larger nationwide share leads to significantly shorter delays. The effect of

SHARE_OD also stays similar. Yet the coefficient for HHI_ORIGIN is now insignificant and the sign switches between specifications.[19]

Mayer and Sinai (2003) argued that airlines may pad their schedule, so that they have extra room in their flight schedules that is not needed. This would make it seem that there are fewer and shorter delays on paper, without affecting the real performance. Therefore, they suggested using excess travel time, which is the travel time of a flight compared to the minimum travel time in a period. We redo our analysis in Table A.6 using the excess travel time compared to the quickest flight between an OD pair in 2016.[20,21] The results for total airline size remain quantitatively the same. For nationwide market share, the coefficient becomes somewhat less negative, while for total FTE and ASSETS, they become more negative. Therefore, larger airlines may actually pad less than smaller ones.[22] In any case, our result on nationwide size is robust, allowing for schedule padding by using excess travel time as the dependent variable. Table A.7 finds that our log-log specifications are also robust to using excess travel time as the dependent variable instead of our original delay measure.

In addition, allowing for padding does not change the effect of route share in a meaningful way: it remains true that a larger route share leads to shorter delays. Allowing for padding does mean that the coefficient for HHI_DESTINATION is consistently negative, and significantly so in most cases. This suggests that more concentration, and thus less competition, leads to shorter delays. For HHI_ORIGIN, in the level specifications the coefficient remains significantly positive, as was the case in our original set-up. However, for the log specification, the coefficient is now insignificant and negative. Therefore, we can conclude that allowing for padding has little to no effect on the coefficients of total size and route share, but does affect the coefficients of the airport HHI.

Finally, Table A.8 estimates a linear probability model for *cancellations*. For all three airline-size measures, a larger overall size seems to lead to fewer cancellations. So also here, a larger total size leads to a higher quality. For concentration at the airport and for route share, we mostly do not find significant effects.[23] Interestingly, when an airport has more departures or arrivals in a month, a flight has a slightly smaller chance of

[19] As the effect for the airport market structure is not robust, we tried re-estimating the models without the HHI_ORIGIN and HHI_DESTINATION. We also tried omitting the congestion variables and the SHARE_OD. The coefficient of the nationwide MARKET_SHARE was hardly affected.

[20] We also did this for the minimum travel time in a month between an OD pair and for the airline-specific minimum time. Results for both alternative variable specifications were similar as here, but the R^2 was lower and s.e.'s were larger.

[21] This sensitivity analysis follows from an excellent suggestion of the reviewer. As our original data set did not contain the actual travel time or cancellations, we regathered our delay data for Tables A.6–A.8 from www.transtats.bts.gov/Tables.asp?DB_ID = 120&DB_Name = Airline%20On-Time%20Performance%20Data&DB_Short_Name = On-Time (accessed on 26 July 2018). For the other variables, the data set is the same as our original data set, and so are the regressions.

[22] Although the result may also be due to a scale change, the average and variance of excess travel time are larger than those of our main independent since they are not corrected for extreme weather. Nevertheless, the results when using excess travel time are qualitatively the same as in our main estimations.

[23] All coefficients are small in an absolute sense. This is probably a scale effect: cancellations are rare, and consequently the cancellation dummy has a very low mean and standard deviation. For instance, if the total market share increases by one percentage point, the probability — which is between zero and one — falls by the tiny amount of 0.000035; but this is 0.4 per cent of the average, which seems quite large and economically significant.

being cancelled. This is the case with all else being equal, including the OD pair fixed effects and month fixed effects. The seasonally fixed effects over the months are larger than the effects of the number of flights, and they indicate that cancellations are most common in January and, to a lesser extent, during the other winter months, July, and August.

We can conclude that the result for the effect of nationwide airline size is robust for transformations of the dependent variable, the independent variables, and the specification; a nationwide larger share of flights leads to shorter and less frequent delays. The effects of the market structure at the airport level are less robust, while again the effect of the share of flights at the route level seems robust.

6.0 Conclusion and Discussion

Air travel delays are the most common category of customer complaints. Therefore, they seem an important part of an airline's service quality. We used two variables on delays: (1) delays in minutes later than scheduled; and (2) whether or not a flight was delayed for more than 15 minutes. We investigated the effect on delays of the total size of an airline in 2016. Total size was measured in three different ways: the share of all US domestic flights; total value of assets; and monthly employment.[24]

A lot of previous research has been conducted on the effect of competition and market share on service quality, and on delays in particular. However, these studies did not consider the total size of an airline. We considered the effects of nationwide size and of competition at the airport and on the route.

Our results suggest that the larger the nationwide size of an airline, the *shorter* and less frequent its delays. Larger airlines also seem to have fewer cancellations. These results seem robust to the choice of specification, controls, variables set-up, and allowing for schedule padding. Larger airlines have more resources, and the efficient use of these may decrease delays.[25]

Our estimations found that if an airline has a larger share of flights *on a route*, then it has *shorter* and *less* frequent delays. The market situation at the airport also plays a role. Our main estimations imply that an origin airport with less competition has longer and more frequent delays. This is the opposite of the results in Mayer and Sinai (2003), and Ater (2012), although Rupp (2006) found something similar. However, our results on the degree of competition at the airport do not seem robust and are not always significant.

To conclude, an increase in the total size of airlines decreases delays. Moreover, there is a clearly separate effect of overall size, and of size or degree of competition at the airport or on the route. Our results indicate that policy makers and consumers do not need to worry about the influence of the nationwide size of an airline on delays and cancellations, as long

[24] Controls were included on the market structure at the airport and route level, on congestion, on month, day, and time of flying, and on characteristics of the airport and aeroplane. We allowed for extreme weather as defined by the US DOT, by subtracting the delay time that was due to extreme weather. This alteration of the independent variable reduced standard errors, while it had little effect on the estimates of the coefficients.

[25] For example, having many aeroplanes at different airports allows an airline to decrease arrival delays: if an aeroplane needs to be used several times a day, but is delayed, all the flights using it will be affected unless there is a replacement.

as there is enough competitiveness at airports. For airline mergers, this suggests that their effect may not be detrimental for consumers. However, as, for example, Steven *et al*. (2016) found, mergers also decrease the competition at the airport and route. Of course, we do not consider prices and other dimensions of quality. These other dimensions of quality may include schedule delay, responsiveness, staff friendliness, baggage handling, and food quality.

Our data set has information on delay time caused by extreme weather, but only for flights delayed 15 minutes or more. Hence, no weather data are available for many of the flights. This may make our measurement of the dependent variable less reliable. For example, the direction of the wind influences the speed and turbulence of aeroplanes, and thereby delays. However, the influence of the missing information may be very limited, as the average extreme weather delay is about 50 minutes. As a check, we also estimated models without subtracting the weather delays. We found very similar estimates for the coefficients of interest, but with larger standard errors. Therefore, the correction for extreme weather seems to make the estimates sharper, but allowing for all types of weather may make the estimates sharper still.

We only considered competition at the airport and between direct flights between OD pairs. Although not directly possible with our data set, it seems interesting to consider competition from indirect hubbing flights and from alternative airports.

References

Ater, I. (2012): 'Internalization of congestion at US hub airports', *Journal of Urban Economics*, 72, 196–209.

Ball, M., C. Barnhart, M. Dresner, M. Hansen, K. Neels, A. Odoni, E. Peterson, L. Sherry, A. Trani, and B. Zou (2010): 'Total delay impact study: a comprehensive assessment of the costs and impacts of flight delay in the United States', National Center of Excellence for Aviation Research, Berkeley. Accessed from www.researchgate.net/publication/272202358_Total_Delay_Impact_Study_A_Comprehensive_Assessment_of_the_Costs_and_Impacts_of_Flight_Delay_in_the_United_States on 28 July 2017.

Borenstein, S. and J. Netz (1999): 'Why do all the flights leave at 8 am? Competition and departure-time differentiation in airline markets', *International Journal of Industrial Organization*, 17, 611–40.

Bowen, B. D. and D. E. Headley (2001): 'Airline Quality Rating Report, paper 14'. Accessed from Purdue e-Pubs at http://docs.lib.purdue.edu/aqrr/14 on 26 July 2017.

Brueckner, J. K. (2002): 'Airport congestion when carriers have market power', *American Economic Review*, 92, 1357–75.

Cao, K. H., B. Krier, and C. M. Liu (2017): 'Nonlinear effects of market structure on service quality: evidence from the U.S. airline industry', *Review of Industrial Organization*, 51, 43–73.

Chen, Y. and P. Gayle (2019): 'Mergers and product quality: evidence from the airline industry', *International Journal of Industrial Organization*, 62, 96–135.

Craig, T. (1988): 'Air traffic congestion: problems and prospects', in J. H. Ausubel and R. Herman (eds.), Cities and their Vital Systems: Infrastructure Past, Present and Future, Washington DC, The National Academies Press, pp. 222–232.

Daniel, J. I. (1995): 'Congestion pricing and capacity of large hub airports: a bottleneck model with stochastic queues', *Econometrica*, 63, 327–70.

Daniel, J. I. and K. T. Harback (2008): '(When) do hub airlines internalize their self-imposed congestion delays?', *Journal of Urban Economics*, 63, 583–612.

Dresner, M. and K. Xu (1995): 'Customer service, customer satisfaction, and corporate performance in the service sector', *Journal of Business Logistics*, 16, 24–40.

Forbes, S. J. and M. Lederman (2010): 'Does vertical integration affect firm performance? Evidence from the airline industry', *The RAND Journal of Economics*, 41, 765–90.

Gal-Or, E. (1983): 'Quality and quantity competition', *The Bell Journal of Economics*, 14, 590–600.
Gil, R. and M. Kim (2016): 'Does competition increase quality? Evidence from the US airline industry', SSRN working paper (version of 17 January 2016), 2617528. Accessed from http://dx.doi.org/10.2139/ssrn.2617528 on 26 July 2018.
Greenfield, D. (2014): 'Competition and service quality: new evidence from the airline industry', *Economics of Transportation*, 3, 80–9.
Gursoy, D., M. H. Chen, and H. J. Kim (2005): 'The US airlines relative positioning based on attributes of service quality', *Tourism Management*, 26, 57–67.
Mayer, C. and T. Sinai (2003): 'Network effects, congestion externalities and air traffic delays: or why not all delays are evil', *American Economic Review*, 93, 1194–1215.
Mazzeo, M. J. (2003): 'Competition and service quality in the US airline industry', *Review of Industrial Organization*, 22, 275–96.
Morrison, S. and C. Winston (2007): 'Another look at airport congestion pricing', *American Economic Review*, 97, 1970–7.
Pai, V. (2010): 'On the factors that affect airline flight frequency and aircraft size', *Journal of Air Transport Management*, 16, 169–77.
Pels, E. and E. T. Verhoef (2004): 'The economics of airport congestion pricing', *Journal of Urban Economics*, 55, 257–77.
Prince, J. T. and D. H. Simon (2017): 'The impact of mergers on quality provision: evidence from the airline industry', *Journal of Industrial Economics*, 65, 336–62.
Rupp, N. (2009): 'Do carriers internalize congestion costs? Empirical evidence on the internalization question', *Journal of Urban Economics*, 65, 24–37.
Rupp, N. G. and K. M. Tan (2018): 'Mergers and product quality: a silver lining from de-hubbing in the U.S. airline industry', SSRN working paper (version of 12 July), 2722782. Accessed from http://dx.doi.org/10.2139/ssrn.2722782 on 26 July 2018.
Rupp, N. G., D. H. Owens, and L. W. Plumly (2006): 'Does competition influence airline on-time performance?', in D. Lee (ed.), *Advances in Airline Economics, Volume 1: Competition Policy and Antitrust*, Amsterdam, Elsevier, pp. 251–72.
Silva, H. E., E. T. Verhoef, and V. A. C. van den Berg (2014): 'Airlines' strategic interactions and airport pricing in a dynamic bottleneck model of congestion', *Journal of Urban Economics*, 80, 13–27.
Steven, A. B., A. A. Yazdi, and M. Dresner (2016): 'Mergers and service quality in the airline industry: a silver lining for air travelers?', *Transportation Research Part E*, 89, 1–13.
Truitt, L. J. and R. Haynes (1994): 'Evaluating service quality and productivity in the regional airline industry', *Transportation Journal*, 33, 21–32.
Yimga, J. O. (2016): 'Airline code-sharing and its effects on on-time performance', *Journal of Air Transport Management*, 58, 76–90.

Appendix

Table A.1
Variables, Definitions, and Descriptive Statistics

Variable	*Definition*	*Mean*	*Std. dev.*
Flights & airports			
DISTANCE	Distance from origin to distance from origin to destination airport, in 1,000 miles	0.82	0.61
OUT_HUB_AIRLINE	Dummy variable = 1 if origin is a hub for the carrier of the specific flight	0.50	0.50
IN_HUB_AIRLINE	Dummy variable = 1 if destination is a hub for the carrier of the specific flight	0.50	0.50
MEDIUM_HUB_ORIGIN	Dummy variable = 1 if enplanements of the origin airport is between 0.25% and 1% of the total number in the USA	0.19	0.39
LARGE_HUB_ORIGIN	Dummy variable = 1 if enplanements of the origin airport is above 1%	0.66	0.47
MEDIUM_HUB_DEST	Dummy variable = 1 if enplanements of the destination airport is between 0.25% and 1% of the total number in the USA	0.19	0.39
LARGE_HUB_DEST	Dummy variable = 1 if enplanements of the destination airport above 1% of the total enplanements in the USA	0.66	0.47
DEPARTURES_ORIGIN	Number of departures from the origin airport in a month	3,295.12	4,482.63
ARRIVALS_DEST	Number of arrivals to the destination airport in a month	3,297.78	4,483.27
Aeroplane characteristics			
AEROPLANE_AGE	Years since the manufacturing year	12.85	6.54
AEROPLANE_CAPACITY	Capacity of aeroplane, in pounds	59,522	55,490
Date characteristics			
MONTH	Dummy variable for month is Jan, … , December		
DAY_OF_WEEK	Dummy variable for day = Monday, … , Sunday		
DEP_TIME	Dummy variable for if departure time is between 00:00–06:00, 06:00–12:00, 12:00–18:00 and 18:00–24:00		
Airline size			
MARKET_SHARE	Number of flights of an airline as percentage of total domestic flights within the USA in percentage	13.85	6.96
TOTAL_ASSETS	Total assets of an airline for a certain month in billions of dollars	25.66	19.62
TOTAL_FTE	Monthly average count of the full-time employees in 10,000 persons (two part-time employees count as one full-time)	4.71	3.46

Table A.1
Continued

Variable	*Definition*	*Mean*	*Std. dev.*
Delay			
ARR_DELAY	Difference between arrival time in minutes and the scheduled time; early arrivals have a zero delay	11.65	37.54
WEATHER_DELAY	Delay time caused by extreme weather, in minutes	2.64	21.09
ARR_DELAY_15	Dummy variable = 1 if the flight arrives 15 minutes or more late than the scheduled arrival time	0.17	0.38
ARR_DELAY_CORR	ARR_DELAY minus WEATHER_DELAY, in minutes	11.19	36.27
Excess travel time	Travel time compared to the shortest time in a year (instead of vs the schedule)	44.30	42.41
Cancellation	Dummy on whether a flight was cancelled	0.01	0.10
Market structure			
HHI_ORIGIN	Herfindahl-Hirschman Index based on the number of departures from an origin airport in a month	0.37	0.21
HHI_DESTINATION	Herfindahl-Hirschman Index based on the number of arrivals at a destination airport in the month of the observation	0.37	0.21
SHARE_OD	Share of the number of flights from an origin airport to a destination airport for an airline in a month	68.72	30.79

Table A.2
Regressions on the Delays with the Total Number of Full-time Employees (TOTAL_FTE) as Independent Variable

	(1) ARR_DELAY_CORR		(2) ARR_DELAY_CORR		(3) ARR_DELAY15	
	coeff.	t-stat	coeff.	t-stat	coeff.	t-stat
TOTAL_FTE	−0.56***	−19.0	−0.61***	−22.1	−0.008***	−21.6
HHI_ORIGIN	−1.47***	−3.81	4.58**	2.84	0.031	1.64
HHI_DESTINATION	−2.78***	−7.60	−0.14*	−0.12	−0.021	−1.51
SHARE_OD	−3.22E-03	−1.14	−0.01***	−3.54	−1.28E-04*	−2.50
DEPARTURES_ORIGIN	−8.16E-06	−0.58	2.20E-04***	3.79	2.54E-06***	3.70
ARRIVALS_DEST	3.12E-05*	2.18	1.62E-04**	2.84	2.31E-06**	3.07
DISTANCE	−0.1.8	−1.13				
AEROPLANE_CAPACITY	1.65E-05***	9.60	1.45E-05***	7.53	7.97E-08**	3.00
AEROPLANE_AGE	0.14***	16.6	1.67E-01***	28.9	1.96E-03***	24.7
IN_HUB_AIRLINE	−0.85**	−3.19	0.10	−0.38	−0.007	−1.91
OUT_HUB_AIRLINE	−1.26***	−4.76	−1.00***	−4.08	−1.27E-04	−0.04
MEDIUM_HUB_ORIGIN	−0.25	−0.84				
MEDIUM_HUB_DEST	1.06***	3.88				
LARGE_HUB_ORIGIN	1.36***	3.86				
LARGE_HUB_DEST	3.00***	8.62				
MONTH dummies	YES		YES		YES	
DEP_TIME dummies	YES		YES		YES	
DAYS_OF_WEEK dummies	YES		YES		YES	
Fixed effects on the OD pair	NO		4,492		4,492	
Observations	4,798,318		4,798,318		4,798,318	
R-squared	0.029		0.029		0.043	

Notes: TOTAL_FTE is in 10,000 of full-time equivalent workers, so two part-time employees add up to one full-time employee. All standard errors were clustered on the combination of origin and destination airport. Significance levels are indicated: * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$. For the panel regressions, the within R^2 gives the part of the variance of the demeaned data that is explained by the model. Coefficients and t-statistics of the dummies for DEP_TIME, DAYS_OF_WEEK, and MONTH are available on request.

Table A.3
Regressions on the Delays with the Total Amount of Assets (TOTAL_ASSETS) as Independent Variable

	(1) ARR_DELAY_CORR		(2) ARR_DELAY_CORR		(3) ARR_DELAY15	
	coeff.	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*
TOTAL_ASSETS	−0.10***	−22.1	−0.10***	−23.9	−0.002***	−26.0
HHI_ORIGIN	−1.57***	−4.1	4.54**	2.80	0.029	1.50
HHI_DESTINATION	−2.89***	−7.98	−0.18	−0.15	−0.023	−1.70
SHARE_OD	−3.94E-03	−1.41	−1.19E-02**	−3.39	−8.03E-05	−1.68
DEPARTURES_ORIGIN	−5.14E-07	−0.04	2.19E-04***	3.78	2.56E-06***	3.73
ARRIVALS_DEST	3.88E-05**	2.75	1.61E-04**	2.82	2.33E-06**	3.09
DISTANCE	−0.07	−0.48				
AEROPLANE_CAPACITY	1.38E-05***	8.16	1.23E-05***	6.34	5.72E-08*	2.17
AEROPLANE_AGE	0.15***	18.3	0.17***	29.6	0.002***	26.5
IN_HUB_AIRLINE	−0.80**	−3.08	−0.13	−0.51	−0.007	−1.90
OUT_HUB_AIRLINE	−1.21***	−4.67	−1.04***	−4.21	2.6E-04	0.07
MEDIUM_HUB_ORIGIN	−0.42	−1.44				
MEDIUM_HUB_DEST	0.89**	3.45				
LARGE_HUB_ORIGIN	1.30***	3.74				
LARGE_HUB_DEST	2.94***	8.68				
MONTH dummies	YES		YES		YES	
DEP_TIME dummies	YES		YES		YES	
DAYS_OF_WEEK dummies	YES		YES		YES	
Fixed effects on the OD pair	NO		4,492		4,492	
Observations	4,798,318		4,798,318		4,798,318	
R-squared	0.029		0.029		0.043	

Notes: TOTAL_ASSETS is in billions of dollars in a month. All standard errors were clustered on the combination of origin and destination airport. Significance levels are indicated: * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$. Coefficients and t-statistics of the dummies for DEP_TIME, DAYS_OF_WEEK, and MONTH are available on request.

Table A.4
Sensitivity Analyses: Excluding Zero Delays and Excluding Weather Correction

	(1) ARR_DELAY_ CORR if >0		(2) ARR_DELAY		(3) ARR_DELAY_ NEW if >0	
	coeff.	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*
MARKET_SHARE	−0.36	−11.46	−0.10	−7.60	−0.27	−9.11
HHI_ORIGIN	9.58	2.68	5.23	3.05	8.31	2.29
HHI_DESTINATION	6.62	2.44	0.77	0.60	6.37	2.22
SHARE_OD	−0.03	−3.76	−3.29	−8.86	−0.03	−3.85
DEPARTURES_ORIGIN	−1.8E-05	−0.12	1.2E-04	1.97	0.00	−1.65
ARRIVALS_DEST	1.1E-04	0.73	1.2E-04	1.99	0.00	−0.03
AEROPLANE_AGE	0.29	24.79	4.2E-06	1.91	0.00	11.72
AEROPLANE_CAPACITY			0.12	20.93	0.28	24.17
IN_HUB_AIRLINE	1.45	2.56	−0.43	−1.56	0.94	1.65
OUT_HUB_AIRLINE	−2.97	−5.62	−1.21	−4.54	−3.20	−5.85
MONTH dummies	YES		YES		YES	
DEP_TIME dummies	YES		YES		YES	
DAYS_OF_WEEK dummies	YES		YES		YES	
Fixed effects on the OD pair	4,492		4,492		4,492	
Observations	1,611,280		4,798,318		1,611,280	
R-squared	0.04		0.03		0.04	

Notes: All standard errors were clustered on the OD-pair airports. Columns (1) and (3) exclude delays that are not positive, and so the number of observations drops substantially.

Table A.5
Regressions with the Logs of the Continuous Variables

	(1) LOG (ARR_DELAY_ CORR)		*(2) LOG (ARR_DELAY_ CORR + 1)*		*(3) LOG (ARR_ DELAY)*	
	coeff.	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*
LOG MARKET_SHARE	−0.05	−6.70	−0.05	−6.63	−0.04	−5.91
LOG HHI_ORIGIN	0.19	4.48	0.03	0.68	−0.02	−0.54
LOG HHI_DESTINATION	0.07	1.92	−0.09	−2.74	0.02	0.47
LOG SHARE_OD	−0.06	−7.11	−0.05	−7.00	−0.04	−6.49
LOG DEPARTURES_ORIGIN	0.40	14.78	−0.04	−1.41	−0.21	−7.53
LOG ARRIVALS_DEST	0.50	19.03	0.07	2.77	−0.06	−2.32
LOG AEROPLANE_CAPACITY	−0.05	−5.83	−0.05	−5.43	0.06	11.7
LOG AEROPLANE_AGE	0.04	14.35	0.04	14.18	0.06	27.1
IN_HUB_AIRLINE	−0.04	−2.28	−0.04	−2.32	−0.02	−1.37
OUT_HUB_AIRLINE	0.00	−0.27	−0.01	−0.32	−0.06	−5.03
Observations	1,611,280		4,798,318		1,611,280	
R-squared	0.05		0.03		0.03	

Notes: All standard errors were clustered on the OD-pair airports. Fixed effects on OD pair, time of day, day of the week, and month included but not shown.

Table A.6
Allowing for Schedule Padding: excess_ travel_time is the Delay Versus the Minimum Travel Time in 2016 Instead Versus the Scheduled Travel Time

	(1) Excess travel time		*(2) Excess travel time*		*(3) Excess travel time*	
	coeff.	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*
MARKET_SHARE	−0.08	−4.29				
TOTAL_FTE			−0.85	−22.38		
TOTAL_ASSETS					−0.14	−25.74
HHI_ORIGIN	6.17	2.78	4.54	2.11	4.38	2.03
HHI_DESTINATION	−2.74	−1.62	−4.40	−2.71	−4.56	−2.82
SHARE_OD	−0.04	−8.52	−0.01	−2.34	−0.01	−1.82
DEPARTURES_ORIGIN	1.6E-04	2.06	0.00	2.43	1.8E-04	2.44
ARRIVALS_DEST	2.6E-04	3.31	0.00	3.68	2.9E-04	3.68
Observations	4,798,318		4,798,318		4,798,318	
R-squared	0.0324		0.0336		0.0338	

Notes: The minimum delay can be — and is for almost all OD pairs — negative. Excess travel time is zero for the best flight(s) and positive for all others. All standard errors were clustered on the combination of origin and destination airport. Fixed effects on OD pair, time of day, day of the week, and month included but not shown. Also included, but not shown, were control on the aeroplane and hubbing.

Table A.7
Allowing for Schedule Padding with Log Variables: EXCESS_TRAVEL_TIME is the Delay Versus the Minimum Travel Time Instead Versus the Scheduled Travel Time

	(1) LOG(EXCESS_ TRAVEL_TIME)		*(2) LOG(EXCESS_ TRAVEL_TIME + 1)*		*(3) EXCESS_ TRAVEL_TIME if > 0*	
	coeff.	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*
(LOG) MARKET_SHARE	−0.02	−4.94	−0.01	−4.92	−0.08	−4.32
(LOG) HHI_ORIGIN	−3.3E-03	−0.18	−4.2E-03	−0.23	6.21	2.80
(LOG) HHI_DESTINATION	−0.07	−3.97	−0.07	−3.99	−2.71	−1.59
(LOG) SHARE_OD	−0.02	−4.53	−0.01	−4.39	−0.04	−8.60
(LOG) DEPARTURES_ORIGIN	−0.01	−0.67	−0.01	−0.66	1.7E-04	2.19
(LOG) ARRIVALS_DEST	0.03	2.30	0.03	2.26	2.7E-04	3.40
Observations	4,792,919		4,798,318		4,792,919	
R-squared	0.0415		0.0412		0.0324	

Notes: The minimum delay can be — and is for almost all OD pairs — negative. EXCESS_TRAVEL_TIME is zero for the best flight(s) and positive for all others. Columns (1) and (2) use logs of the dependent and independent variables; column (3) uses levels, but only considers delays that are larger than the minimum delay. All standard errors were clustered on the combination of origin and destination airport. Fixed effects on OD pair, time of day, day of the week, and month included but not shown. Also included, but not shown, were control on the aeroplane, airport, and hubbing.

Table A.8
Effect of the Total Size of an Airline on Cancellations

	(1) Cancelled		*(2) Cancelled*		*(3) Cancelled*	
	coeff.	*t-stat*	*coeff.*	*t-stat*	*coeff.*	*t-stat*
MARKET_SHARE	−3.5E-05	−0.53				
TOTAL_FTE			−1.2E-03	−10.01		
TOTAL_ASSETS					−2.0E-04	−10.51
HHI_ORIGIN	6.8E-03	1.53	4.4E-03	1.00	4.2E-03	0.96
HHI_DESTINATION	7.1E-03	2.20	4.6E-03	1.47	4.4E-03	1.41
SHARE_OD	−3.1E-05	−2.17	1.8E-05	1.19	2.1E-05	1.37
DEPARTURES_ORIGIN	−9.4E-07	−5.36	−9.0E-07	−5.11	−9.0E-07	−5.11
ARRIVALS_DEST	−1.1E-06	−5.91	−1.0E-06	−5.66	−1.0E-06	−5.66
Observations	4,856,995		4,856,995		4,856,995	
R-squared	0.1717		0.1721		0.1722	

Note: The cancelled dummy is 1 if the flight was cancelled. All standard errors were clustered on the combination of origin and destination airport. Fixed effects on OD pair, time of day, day of the week, and month were included but not shown. Also included, but not shown, are the controls on the aeroplane, airport, and hubbing.