Competition and Service Quality in the U.S. Airline Industry

Michael J. Mazzeo[1]
Kellogg Graduate School of Management — Northwestern University

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I. Introduction

Deregulation of commercial airline transportation in the United States has contributed to a striking overhaul in an industry that is crucially important to the American economy. Economists predicted that unregulated competition among airlines would result in lower costs and reduced fares for consumers. It was also hoped that consumers would benefit as competing airlines offered improved levels of service to attract demand. While the skies have been somewhat bumpy for carriers — particularly those unable to successfully cut costs — the most efficient airlines have been able to thrive in the two decades since deregulation.

One concern that accompanied deregulation was that scale economies inherent in air transport would substantially reduce the number of airlines operating in a competitive system. If the concentration of particular markets were to increase as a result, consumers might be vulnerable to higher prices. Indeed, academic studies of airline fares have demonstrated that while deregulation has reduced most fares, prices are lower when the number of airlines flying between a given pair of cities is larger. The interplay between cost savings from scale and the potential threat of high fares due to the exercise of market power has informed the debate over airline competition policy since deregulation.

Recent government overtures toward re-regulation of the airline industry have focused on the underprovision of service, rather than high fares. Both the executive and legislative branches

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have applied pressure on the industry by threatening to impose strict requirements on the quality of service airlines provide. To avert passage of a "Passengers' Bill of Rights" last year, the industry made promises to improve service quality that temporarily mollified supporters of re-regulation. However, the industry's failure to improve service — in particular, their worsening record of delayed and cancelled flights — has prompted many prominent legislators continue to push for government intervention into the competitive landscape.

It is interesting to note that policy makers are continuing to closely monitor concentration within the airline industry, though not necessarily making the connection between concentration and service quality. The U.S. Department of Justice recently pursued a case against American Airlines, asserting that they engaged in illegal practices to maintain monopoly status on specific routes to and from the Dallas-Fort Worth Airport. The proposed merger between United Airlines and USAir — which many analysts believe would precipitate further industry consolidation — is currently undergoing intense scrutiny by antitrust authorities. That the primary focus of such inquiries is the effect of concentration on price is not surprising. However, I would expect more attention to be focused on the potential effects on service quality, particularly given the simultaneous call for action regarding flight delays.

The goal of this paper is to systematically examine the connection between high market concentration and poor airline service. The analysis will focus on on-time performance and flight cancellations — the most common categories of customer complaints — on a route-by-route basis using data from the Airline Information database maintained by the U.S. Bureau of Transportation Statistics. Airlines have argued that weather conditions beyond their control are the cause of most delays and cancellations; I will incorporate data from the National Weather Service to control for such problems. Critics, however, argue that airlines have considerable flexibility regarding schedule changes. Delays and cancellations are often imposed on consumers who have fewer alternatives. I will be able to address this particular allegation by comparing on-time performance with measures of competitiveness across the various routes.

II. Background on Quality and Competition

Over the past several years, considerable attention has been devoted to service levels in the U.S. airline industry — with the predominant view that quality is poor and rapidly deteriorating. While the industry has been deregulated for 15 years, substantial monitoring of firm conduct continues. In part, this results from the high concentration that (associated with airlines' hub-and-spoke route system) persists in many travel markets.[2] The industry also seems to be a popular target for politicians. Since early 1999, the U.S. Congress has held numerous hearings on service problems, pressured the airlines to agree to a new "Airline Customer Service Commitment," and subsequently held additional hearings after service levels failed to improve. I focus here on on-time performance as a proxy for service quality, as most industry observers do.[3]

While weather, congestion and other exogenous factors certainly contribute to air delays, the lack of competition in many airline markets potentially reduces firms' incentives to invest in improving on-time performance. Under reasonable conditions, it is straightforward to show that a monopolist will underprovide quality when some price regulation is imposed on the firm.[4] The airline industry is not price regulated, of course, but airlines' ability to charge the monopoly price

[2] As detailed in the next section, more that half the routes in the dataset examined here are served directly by only one firm.

[3] For example, in their widely cited "Airline Quality Rating" series, Bowen and Headley (2001) devise an overall quality metric composed mostly of flight delay rates and factors that are exacerbated by delayed flights (e.g., customer complaints, lost baggage). Dresner and Xu (1995) also find a connection between delayed flights and customers filing complaints on those flights.

[4] This result, for example, is derived by Spence (1975). In his paper, a fixed-price monopolist provides less than the socially optimal level of quality. In the case where the cost of providing additional quality increases slower than the demand as a function of quality, however, a profit-maximizing monopolist would provide the highest possible quality level.

is likely inhibited by attention from anti-trust authorities. As such, we may expect to observe lower quality when firms face less competition.

The question of quality provision in monopoly markets has been addressed empirically in several other industries. For example, Hoxby (2000) finds that metropolitan areas with more school districts have higher quality in terms of student achievement. Dranove and White (1994) summarize the evidence of the connection between quality provision and market competition in hospital markets and Domberger and Sherr (1989) look at markets for legal services. An early airline industry study by Douglas and Miller (1974) investigates flight frequency as the measure of quality across city pair markets. Borenstein and Netz (1999) note that airlines did not necessarily choose to schedule their flights at passengers' most preferred times during the period of price regulation.

A recent paper by Suzuki (2000) suggests a model of consumer behavior that could underlie the firm response I consider in the empirical analysis. In his model, passengers' propensity to switch airlines increases if they have experienced prior flights delays. He calibrates the model using data from the Atlanta-O'Hare city pair market and finds that fluctuations in market share between American, Delta and United from 1990 to 1997 can be explained by passengers' experiences with prior flight delays. Evidence such as this suggests that the consequences of poor on-time performance can be substantial in competitive markets — we might expect firms to allocate their resources in such a way as to achieve better on-time performance on more competitive routes.[5]

[5] Foreman and Shea (1999) find evidence that average airline on-time performance improves after on-time rates are published. They also find a positive correlation between on-time performance and competition, but their competition measure is very crude.

III. Data

The data for this analysis were put together from a variety of sources. Partially in response to the growing concern over air traffic delays, the U.S. government has been compiling and publishing more detailed information about the on-time performance of airlines. Several airline and travel websites will present the average "on-time" performance — percentage of flights less than 15 minutes late, rounded to the nearest 10 percent — of each flight to consumers along with details about price, schedule and equipment. On a monthly basis, the Department of Transportation publishes the "Air Traffic Consumer Report," which includes summary statistics on flight delays, as well as mishandled baggage, oversales and customer complaints. The Bureau of Transportation Statistics (BTS) maintains a more extensive compendium of information. The BTS's Office of Airline Information tracks the entire domestic system of the ten major U.S. airlines (Alaska, America West, American, Continental, Delta, Northwest, Southwest, TWA, United and USAir). The airlines submit their entire flight schedules and subsequently provide the actual gate departure and arrival times for each flight.

The data are available to download from the BTS website — the dataset used for this analysis contains all the flights scheduled between 50 major airports in January, April, and July of 2000. The airports were selected to include all of the major airline hubs and a sample of facilities in smaller cities. The airports, and the number of flights in the dataset taking off and landing from each, are listed in Table 1.

As discussed above, the summary data typically report a flight as "late" if it arrives at the gate more than 15 minutes past its scheduled arrival time. The flight level data report adherence to schedule rounded to the nearest minute, which permits a more accurate analysis. The average flight in the dataset was 10.7 minutes late. Figure 1 displays the frequency of observations in 15-minute intervals around their scheduled arrival time. It is interesting to note that quite a few of the flights recorded were "early" — 9.7 percent of flights reached their gate prior to the scheduled

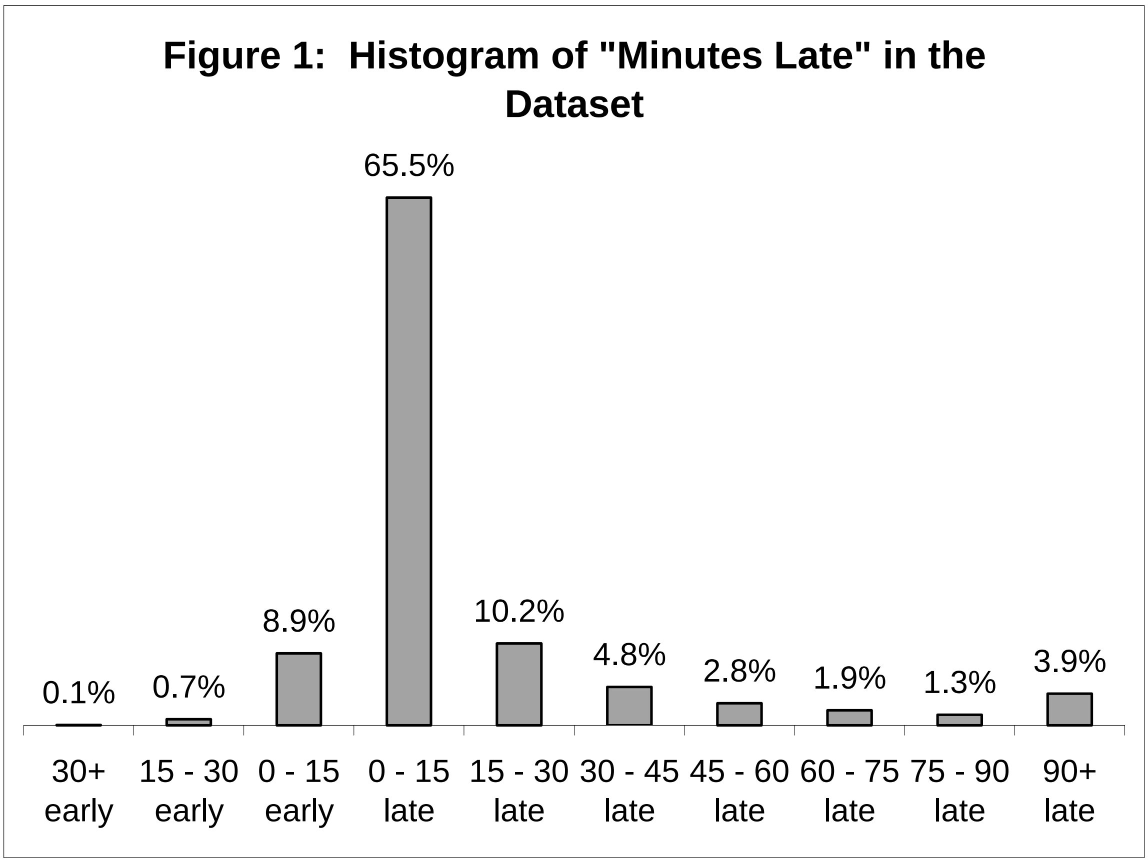
Table 1: Summary of Airports, Flights and Carriers in the Dataset

Airport	Outbound Flights	Inbound Flights	Share of Total Flights by Carrier: Alaska	Am. West	American	Continental	Delta	Northwest	Southwest	TWA	United	US Air
Albuquerque (ABQ)	6603	6118	0.0%	8.1%	7.4%	6.9%	11.0%	2.8%	46.8%	0.0%	10.4%	0.0%
Atlanta (ATL)	44469	33523	0.0%	1.0%	3.5%	4.0%	77.6%	3.5%	0.0%	1.4%	4.2%	4.8%
Birmingham (BHM)	3659	3952	0.0%	0.0%	5.0%	4.5%	22.1%	11.0%	42.0%	0.0%	3.3%	12.1%
Boise (BOI)	2504	2506	0.0%	7.2%	0.0%	0.0%	13.3%	8.6%	39.5%	0.0%	31.4%	0.0%
Boston (BOS)	24222	25336	0.0%	2.9%	12.6%	8.9%	21.8%	6.8%	0.0%	2.6%	15.9%	28.5%
Buffalo (BUF)	4240	4489	0.0%	0.0%	7.8%	9.9%	8.5%	13.6%	0.0%	0.0%	10.5%	49.7%
Charlotte (CLT)	20382	20813	0.0%	0.0%	1.9%	1.6%	2.6%	3.1%	0.0%	1.8%	1.9%	87.0%
Chicago O'Hare (ORD)	55231	50100	0.0%	1.2%	34.1%	3.1%	3.5%	4.3%	0.0%	1.7%	48.6%	3.5%
Cleveland (CLE)	10878	11175	0.0%	0.9%	3.3%	56.4%	6.6%	8.3%	6.4%	3.7%	6.8%	7.6%
Cincinnati (CVG)	14238	14565	0.0%	0.0%	1.3%	0.2%	91.8%	0.7%	0.0%	2.4%	3.7%	0.0%
Columbus (CMH)	8036	8337	0.0%	16.6%	3.0%	6.3%	16.2%	10.4%	8.6%	6.6%	8.8%	23.4%
Dallas (DFW)	42026	34080	0.0%	1.4%	66.7%	4.1%	15.5%	3.2%	0.0%	2.1%	4.7%	2.3%
Denver (DEN)	26392	27859	0.0%	2.4%	4.8%	4.2%	6.1%	3.7%	0.0%	2.1%	73.9%	2.8%
Des Moines (DSM)	1557	1619	0.0%	0.0%	9.8%	0.0%	0.0%	5.7%	0.0%	33.1%	51.3%	0.0%
Detroit (DTW)	26070	26776	0.0%	1.7%	3.5%	3.7%	2.9%	74.9%	3.0%	2.1%	4.0%	4.4%
Hartford (BDL)	7060	7519	0.0%	1.7%	9.8%	5.1%	17.7%	10.2%	3.7%	5.2%	14.9%	31.7%
Honolulu (HNL)	2789	2917	0.0%	0.0%	16.7%	9.7%	18.6%	19.9%	0.0%	3.3%	31.9%	0.0%
Houston (IAH)	23617	24791	0.0%	2.3%	5.1%	73.5%	2.9%	4.5%	0.0%	1.5%	5.9%	4.2%
Indianapolis (IND)	7782	8132	0.0%	3.6%	3.2%	7.2%	10.8%	20.1%	11.1%	7.0%	13.4%	23.7%
Jacksonville (JAX)	4537	4927	0.0%	0.0%	4.0%	10.9%	23.3%	10.1%	16.0%	6.0%	4.1%	25.6%
Las Vegas (LAS)	24276	25204	3.6%	24.2%	5.5%	6.1%	9.4%	4.2%	28.2%	2.1%	14.5%	2.2%
Lexington (LEX)	778	904	0.0%	0.0%	0.0%	0.0%	65.8%	0.0%	0.0%	0.0%	0.0%	34.2%
Los Angeles (LAX)	39546	41530	5.6%	6.1%	16.0%	4.7%	9.7%	4.5%	12.3%	2.2%	35.9%	3.1%
Louisville (SDF)	4386	4704	0.0%	0.0%	4.2%	3.9%	26.8%	11.2%	19.9%	9.5%	2.8%	21.7%
Memphis (MEM)	10228	10695	0.0%	0.0%	2.9%	0.0%	9.6%	79.2%	0.0%	0.0%	3.8%	4.4%

Table 1: Summary of Airports, Flights and Carriers in the Dataset (cont.)

Airport	Outbound Flights	Inbound Flights	Share of Total Flights by Carrier: Alaska	Am. West	American	Continental	Delta	Northwest	Southwest	TWA	United	US Air
Miami (MIA)	14683	15714	0.0%	1.3%	53.9%	7.7%	6.5%	6.1%	0.0%	4.5%	10.8%	9.2%
Minneapolis (MSP)	25069	25831	0.0%	1.7%	4.1%	2.7%	3.6%	74.4%	0.0%	3.3%	7.4%	2.9%
Nashville (BNA)	10316	10969	0.0%	0.0%	12.7%	4.1%	13.2%	11.3%	37.3%	5.0%	4.4%	12.1%
New Orleans (MSY)	9356	9872	0.0%	0.3%	8.2%	16.6%	15.7%	8.5%	24.8%	5.5%	9.7%	10.7%
New York Kennedy (JFK)	9320	9488	0.0%	7.5%	23.3%	0.0%	29.3%	4.1%	0.0%	18.6%	17.3%	0.0%
New York LaGuardia (LGA)	20570	22396	0.0%	0.0%	16.1%	6.3%	25.4%	8.4%	0.0%	2.9%	12.7%	28.2%
Newark (EWR)	24907	26063	0.0%	3.3%	7.5%	55.3%	9.2%	6.8%	0.0%	2.2%	10.8%	5.0%
Oklahoma City (OKC)	3103	3367	0.0%	0.0%	15.4%	11.2%	15.6%	9.6%	16.9%	17.0%	14.4%	0.0%
Omaha (OMA)	3588	3816	0.0%	11.3%	6.8%	2.5%	4.8%	17.5%	16.6%	14.7%	25.9%	0.0%
Orlando (MCO)	19865	20723	0.0%	1.0%	7.4%	8.7%	34.2%	7.4%	8.3%	4.9%	10.2%	17.8%
Philadelphia (PHL)	22440	23549	0.0%	2.0%	5.8%	3.2%	7.0%	6.4%	0.0%	2.3%	10.2%	63.1%
Phoenix (PHX)	30783	33458	3.1%	39.3%	3.8%	3.4%	5.9%	3.6%	26.5%	1.9%	9.9%	2.7%
Pittsburgh (PIT)	17369	17394	0.0%	0.0%	1.1%	1.7%	3.6%	2.8%	0.0%	2.9%	3.1%	84.9%
Portland (PDX)	10140	10403	22.4%	5.7%	3.6%	2.9%	17.1%	5.3%	11.5%	3.0%	28.5%	0.0%
Raleigh (RDU)	7763	8446	0.0%	0.0%	12.5%	8.4%	15.2%	10.4%	9.3%	4.5%	5.0%	34.8%
Richmond (RIC)	3796	4215	0.0%	0.0%	3.2%	6.8%	18.0%	8.7%	0.0%	4.3%	11.2%	47.8%
Sacramento (SMF)	7171	7338	6.3%	8.4%	3.4%	0.9%	6.4%	3.1%	46.3%	3.0%	22.4%	0.0%
St. Louis (STL)	28150	29185	0.0%	0.7%	2.8%	1.3%	2.1%	3.5%	12.4%	71.7%	2.7%	3.0%
Salt Lake City (SLC)	14591	15251	0.0%	2.9%	2.5%	2.0%	62.6%	2.2%	16.7%	1.9%	9.2%	0.0%
San Diego (SAN)	14187	15032	7.5%	6.4%	8.4%	5.4%	9.2%	4.4%	29.3%	3.0%	22.6%	3.9%
San Francisco (SFO)	27925	28726	5.0%	3.6%	10.3%	4.8%	7.4%	4.9%	4.6%	2.2%	53.8%	3.6%
Seattle (SEA)	16944	17500	29.1%	3.8%	6.1%	4.5%	9.0%	9.4%	8.0%	3.2%	23.4%	3.6%
Tampa (TPA)	12432	13236	0.0%	1.5%	8.1%	10.4%	20.1%	8.5%	15.4%	4.5%	8.3%	23.3%
Washington Dulles (IAD)	15545	16036	0.0%	0.1%	5.6%	1.3%	7.6%	5.0%	0.0%	2.3%	54.7%	23.6%
Washington National (DCA)	17581	18639	0.0%	0.9%	12.3%	10.4%	20.5%	9.5%	0.0%	3.4%	8.2%	34.6%

arrival time. This does suggest that a certain amount of slack may be built into the airlines' schedules; we will consider whether this may be done strategically below. On the other hand, an almost identical 9.8 percent of flights in the dataset were 45 minutes or more late. To the extent that passengers' frustration with poor service grows by the minute, it will be useful to investigate the continuous measure of on-time performance.



To isolate the effect of market structure on on-time performance, it is useful to account for factors that affect the ability to adhere to schedule, but over which carriers have less control. Weather is the primary example, as particular weather conditions may require additional preparations for takeoff or landing or may limit the use of the full complement of an airport's runways. The National Weather Service (NWS) maintains an archive of daily atmospheric conditions at various sites throughout the country that is also accessible through the Internet. Conveniently, the reporting site for a particular city is typically its airport — all 50 airports selected have archived data on the NWS website. For each of the 92 days represented in the flight data, I have collected the average, minimum and maximum temperature for each airport. The NWS also maintains records on "significant" weather; I know if rain, snow, fog, haze, or thunderstorms were reported at each airport on each day.

Airport congestion is also cited as an explanation for poor on-time performance. To be sure, airlines do have at least some control over airport congestions levels — airports become more congested as individual airlines schedule additional flights. However, the airlines do not control the schedules of their competitors and most airports do vary in the their congestion levels at different times of the day. Furthermore, airlines' schedules are set well in advance of other decisions (crew deployment, aircraft utilization) carriers make that potentially affect on-time performance. I have constructed the variable CONGEST to equal the number of flights (from all U.S. airports) scheduled to land at the same airport during the same hour as each flight in the dataset. I will also include airport fixed effects in the regressions to control for capacity and other airport-specific factors that I cannot measure directly.

The flight level on-time data kept by the BTS also includes the "tail number" of the aircraft that flew on each completed flight. The tail number is a unique aircraft identifier that was matched to the U.S. Civil Aviation Registry maintained by the Federal Aviation Administration (FAA). For each aircraft, the FAA data contains ownership information, manufacturer and model of the aircraft and its engines, the year the plane was manufactured, and the maximum number of seats possible on the plane. Matching these data with the flight level dataset can allow us to investigate whether aircraft characteristics (e.g., age) are correlated with on-time performance. It would also be possible to determine whether aircraft are deployed strategically — older planes on less competitive routes, for example.

Finally, I created a couple of alternate market structure measures to use to test the basic hypothesis that carriers keep their schedules less closely in less competitive markets. For each of the 2,450 origin/destination pairs, I have counted up how many of the ten airlines provide nonstop service between the two airports. These is considerable variety in the degree of direct competition across the markets, as displayed below:

Number of Airlines Offering Non-Stop Service	Number of "Airport-Pair" Routes
0	1,088
1	837
2	418
3	87
4	16
5	2
6	2
Total	2,450

For about 44 percent of the airport pairs, no airline provides nonstop service. For some close airport pairs service is impractical (e.g., no airline flies from Kennedy to LaGuardia or from Dulles to National). For many others, no airline flies nonstop, but several airlines offer connecting service (e.g., between San Diego, CA and Richmond, VA). Among the airport pairs where nonstop service is offered, there is only one option just over 60 percent of the time. On the remaining routes, consumers have the ability to select from two or more carriers.

I also constructed measures of the share of total traffic accounted for by each airline at each airport. Passengers dissatisfied with poor on-time performance likely travel to several cities from their home airport, so it will by crucial to incorporate the consumers' ability to choose an alternative carrier on other routes as well. This is particularly true in markets where there is relatively little direct service. Returning to Table 1, we see that airport concentration varies substantially. At one extreme is Oklahoma City, a small airport where seven of the ten airlines are represented and each has between 10 and 17 percent of the total flights. On the other hand, several of the hub airports are dominated by a single airline — USAir represents 87 percent of the flights in and out of Charlotte, while over 91 percent of Cincinnati's flights are on Delta.

IV. Empirical Analysis

This section contains empirical analyses of service quality using the data described above. In Table 2, I present reduced-form estimations with various measures of on-time performance as the dependent variable. The first panel is an OLS regressions of "Minutes Late;" the second and third are probits predicting whether a flight is 15 and 45 or more minutes late, respectively. For each estimation, the unit of observation is an individual flight. Due to some missing observations in the various merged datasets, the analysis sample is somewhat smaller than the total population of flight information from the BTS.

As expected, the most significant predictors of on-time performance are the weather variables. In particular, if thunder, snow, rain or fog is reported at either the origin or destination airport, the flight has a statistically significant chance of being delayed. The delay is particularly long — more than 14 minutes on average — on a day with thunderstorm activity. Cold weather appears to reduce delays; however, this result may show up because days with a very low minimum temperature also have several hours where temperatures are warm enough not to affect flight preparations.

I also included some variables that might be correlated with more direct costs of flight delays to the airlines. The "Into Hub" and "Out of Hub" dummy variables demonstrate an interesting dichotomy.[6] When flights into a hub are significantly delayed, airlines incur costs to rebook passengers on connecting flights, monitor interrupted baggage, etc. In addition, a

[6] Flights into hubs were the following carrier/destination pairs: America West/Las Vegas, Phoenix; American/O'Hare, Dallas; Continental/Cleveland, Houston, Newark; Delta/Atlanta, Cincinnati, Salt Lake City; Northwest/Detroit, Memphis, Minneapolis; TWA/St. Louis; United/O'Hare, Denver, Los Angeles, Dulles, US Air/Charlotte, Philadelphia, Pittsburgh.

passenger's delay after missing a connecting flight is substantially compounded. It is not surprising, then, to find that flights into hubs have significantly fewer delays. The flights out of hubs are similar to others in the dataset. In a similar vein, one might expect airlines to be more vigilant about keeping to their schedules on flights carrying more passengers. While I do not know the number of consumers on each flight, there are data on the capacities of the aircraft used. The evidence is mixed here —the number of seats on the aircraft comes in positive and significant, but very large planes (jumbo equals one if the number of seats exceeds 200) are on time more often.

The last two rows of Table 2 contain the key variables of interest in evaluating the hypothesis that airlines have fewer on-time flights on their least competitive routes. The estimates here do provide empirical support for this hypothesis, as both the airport share (percent of flights from the origin and destination airports the carrier represents) and the SOLO dummy (equals one if there is only one carrier flying direct on the route) are positive and significant in both the minutes late regression and the on-time probits. The effects are not economically large, however. A flight on a monopoly route is on average less than a minute later than on a competitive route, and if the carrier has 15% greater origin or destination market share the average delay on the flight increases by one minute. Put another way, the estimates in the middle panel of the table indicate that a particular flight is about as likely to be 15 minutes late if it is operated by the only carrier that flies between the two cities as if fog is reported on the day of the flight. Flights on foggy days are equally likely to be 45 minutes late as 15 minutes late, but the SOLO variable's effect drops off somewhat in the 45-minutes late probit.

Finally, some control variables were included in these estimations, including airport and airline fixed effects. The airline effects mirror the raw numbers (as reported by Bowen and Headley, for example) for United and America West, but the Southwest Airlines dummy variable is positive and significant. The may be indicative of Southwest's strategy to select routes based in part on their potential for keeping flights on schedule. Southwest also attempts to avoid congested airports; the congestion variable is also strongly associated with flight delays. The results also appear to indicate that delays are getting worse over time (January is the omitted month), but this cannot be distinguished from seasonal variation with only one year's data.

There are several potential sources of endogeneity in these estimations; Tables 3 and 4 address two of them. Table 3 presents a regression whose dependent variable is the scheduled elapsed time for each flight in the dataset. Airlines have been criticized for "padding" their schedules to avoid missing their scheduled arrival times; this could potentially bias the results from Table 2. Of course, scheduled time is prescribed mostly by the flight's distance (miles) and direction ("to east" equals 1 if the flight travels from west to east, -1 from east to west, and the fraction in between for intermediate compass points). The schedules also appear to reflect realities regarding congestion and time of day effects. It is interesting to note that flights out of the hub have a longer than scheduled flight time on average, while flights into the hub do not. This may partially explain the negative coefficient in on "Out of Hub" in the minutes late regression.

There are mixed results for the concentration variables. SOLO flight schedules appear to be padded; as a result, the SOLO coefficient may be biased downward in the on-time estimations. The airport share variable, however, is negative and significant. While airport and airline dummies are included, there may be interactions correlated with airport share that affect scheduling. For example, a dominant carrier may have access to more convenient airport gates. The data for scheduled time on the runway are not available, but I do know the actual "taxi in" times for the flights in the dataset. There is a significant negative correlation between taxi in time and airport share, which may be reflected in scheduling.

The correlation between on-time performance and concentration is suggestive; however, the estimations presented do not indicate exactly the behavior that airlines engage in to generate these results. One potential explanation is the aircraft deployed — with a limited fleet that varies in its reliability, airlines might choose to use less reliable aircraft where the cost of delay is less acute. Aircraft age is a possible proxy for reliability; in fact Table 2 indicates that a flight is more likely to be delayed if an older plane is used. Table 4, however, indicates that significantly younger planes are used by carriers on their monopoly routes and to/from their dominant airports. Further investigation will attempt to tease out from the data a behavioral choice by the carriers that helps explain the difference in outcomes across routes with different levels of market concentration.

One potential source of endogeneity that is as yet not addressed is the market concentration measures themselves. Clearly there is variety in the entry strategies of firms across the various city-pairs in the dataset — to the extent that this is correlated with the ability to remain on-time, there is bias in a regression of on-time performance on market concentration. In other work (Mazzeo, 2001), I have addressed the potential endogeneity of market structure in outcome regressions by estimating a separate market structure model. The networked nature of the airline industry might complicate such a model, but there is potential for correcting any bias using such a procedure.

Table 2: Reduced-Form Models of Airline On-Time Performance

Flight-level Regressions — Number of Observations = 630,389

	OLS Regression Dep. Var. = Minutes Late			Probit Model Dep. Var. = I (Minlate > 15)			Probit Model Dep. Var. = I (Minlate > 45)		
	Coef.	StdErr.	t	Coef.	StdErr.	z	Coef.	StdErr.	z
Constant	-8.313	0.604	-13.76	-1.382	0.023	-60.39	-1.950	0.029	-66.23
April	0.490	0.134	3.67	0.009	0.005	1.73	-0.035	0.007	-5.17
July	4.320	0.175	24.67	0.156	0.006	23.37	0.132	0.008	15.51
Cold	-4.063	0.149	-27.23	-0.121	0.006	-21.04	-0.190	0.008	-25.33
Thunder	14.22	0.142	99.92	0.427	0.005	81.65	0.497	0.006	78.44
Rain	6.646	0.134	49.33	0.271	0.005	54.37	0.278	0.006	44.69
Snow	9.575	0.176	54.36	0.369	0.007	56.40	0.377	0.008	46.02
Fog	1.861	0.127	14.70	0.084	0.005	17.30	0.085	0.006	13.62
Haze	-0.402	0.119	-3.66	-0.026	0.004	-6.22	-0.017	0.005	-3.24
Into Hub	-6.149	0.245	-25.07	-0.224	0.009	-24.66	-0.194	0.011	-17.12
Out of Hub	-1.892	0.244	-7.75	-0.000	0.009	-0.01	-0.004	0.011	-0.31
Aircraft Age	0.184	0.008	23.31	0.047	0.000	15.76	0.006	0.000	15.96
# of Seats	0.027	0.002	12.68	0.001	0.000	11.89	0.000	0.000	4.77
Jumbo	-4.743	0.408	-11.63	-0.159	0.015	-10.38	-0.138	0.020	-7.07
Congest	0.090	0.004	23.29	0.004	0.000	26.85	0.003	0.000	17.32
Airport Share	6.397	0.435	14.70	0.162	0.016	9.92	0.109	0.021	5.29
SOLO	0.769	0.144	5.33	0.060	0.005	10.92	0.047	0.007	6.77
Airline Dummies	Yes			Yes			Yes		
Airport Dummies	Yes			Yes			Yes		

Table 3: Reduced-Form Regression of Airline Flight Scheduling

Flight-Level Regressions — Number of Observations = 764,296

Dependent Variable = "Scheduled Elapsed Time" for Each Flight

	Coefficient	Standard Error	t-Statistic
Constant	34.429	0.099	349.34
April	-0.779	0.024	-32.27
July	-1.974	0.024	-82.66
Into Hub	0.090	0.048	1.86
Out of Hub	1.623	0.048	33.87
Time of Day	5.258	0.045	115.73
Congest	0.114	0.001	140.39
Airport Share	-1.121	0.083	-13.58
Solo	0.337	0.030	11.15
"To East"	-10.301	0.013	-780.12
Miles	0.118	0.000	6187.93
Airline Dummies		Yes	
Airport Dummies		Yes	

Table 4: Reduced-Form Regression of Age of Deployed Aircraft

Flight-Level Regressions — Number of Observations = 630,389

Dependent Variable = Age of Aircraft Deployed on Each Flight

	Coefficient	Standard Error	t-Statistic
Constant	16.166	0.088	183.86
April	-0.097	0.022	-4.33
July	-0.341	0.022	-15.36
Into Hub	-0.288	0.471	-6.12
Out of Hub	-0.300	0.468	-6.41
Congest	-0.004	0.001	-5.17
Airport Share	-0.844	0.083	-10.16
Solo	-1.896	0.028	-68.80
Airline Dummies		Yes	
Airport Dummies		Yes	

V. Conclusions

With several mergers under consideration and increased threat of government intervention, now is a very crucial time for policy analysis of the U.S. airline industry. Unlike previous studies that focused on prices, this paper examines the hypothesis that dominant carriers use their market power to impose lower quality of service — through increased flight delays — to their customers. Margins may be higher on monopoly routes, because airlines that do not face competitive pressure can save the costs that would be needed to provide higher quality, on-time service. The results in this paper indicate that, in fact, flights are less frequently on time on routes that are served by only one airline and in cases where the carriers market share at the airports served are higher. Accounting for scheduling suggests that the actual quality provided is even worse; the airlines schedule longer flight times on their monopoly routes, all else equal.

Further work will be done to uncover the mechanism through which the observed patterns of flight delays and concentration help airlines to save costs. One potential explanation — the age of aircraft deployed — does not have much empirical support. In so doing, we may better understand the incentives of airlines when making and adhering to their schedules and appreciate the potential connection between market structure regulation and the provision of quality service for the public. More broadly, this study is among the first to quantify the link between competition and product quality, which will inform policy makers when assessing the competitiveness of markets, evaluating potential mergers, and imposing industry standards.

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