Review of Industrial Organization **22:** 275–296, 2003.

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

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Abstract. The U.S. government, media, and flying public have expressed great concern in recent years over both airline market concentration and flight delays. This study explores potential connections between the two by examining whether the lack of competition on a particular route results in worse on-time performance. Analysis of data from the U.S. Bureau of Transportation Statistics in 2000 indicates that both the prevalence and duration of flight delays are significantly greater on routes where only one airline provides direct service. Additional competition is correlated with better on-time performance. Weather, congestion, and scheduling decisions also contribute significantly to explaining flight delays.

Key words: Airlines, competition, flight delays, quality.

JEL Classifications: L13, L43, L93

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 might hold down entry and leave the number of airlines operating in a competitive system relatively small. If particular markets were concentrated as a result, consumers would be vulnerable to higher prices. Indeed, studies of airline pricing have demonstrated that while deregulation has reduced most fares, prices are lower when the number of airlines flying between a given pair of cities

* Thanks to Meghan Busse, Cory Capps, participants at the IDEI/CSIO workshop in Toulouse, two anonymous referees, and the editor John Kwoka for very useful insights. Special thanks to Scott Schaefer for his assistance and suggestions.

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.[1]

A separate set of recent government overtures toward re-regulation has focused on the underprovision of service by the airline industry. Both the executive and legislative branches 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" in 2000, the industry made promises to improve service quality, temporarily mollifying 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 have precipitated further industry consolidation – was scrapped after intense scrutiny by antitrust authorities. That the primary focus of such inquiries is the effect of concentration on price is not surprising. However, one might expect more attention to be focused on the potential effects on service quality, particularly given the simultaneous call for action regarding flight delays.

This paper systematically examines the connection between high market concentration and poor airline service. The analysis focuses on on-time performance – the most common category of customer complaints – on a flight-by-flight 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; 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 will hurt airlines' profitability less if they are imposed on consumers who have fewer alternatives. I address this particular assertion by comparing on-time performance with measures of competitiveness across the various routes. The findings indicate that flight delays are more common and longer in duration on routes where only one airline provides direct service and through airports where the carrier represents a larger share of total flights. This suggests that airlines may lack sufficient incentive to provide service quality in markets where they do not face competition.

[1] Borenstein's (1992) survey provides a summary of the important results.

II. Quality, Competition and Airlines

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 crusading 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 many industry observers do.[3]

Weather, congestion and other exogenous factors undoubtedly contribute to air delays. Nevertheless, airlines could take actions or make investments that would improve their on-time performance. For example, a delay caused by a failed pre-flight maintenance inspection could be mitigated if an extra, unscheduled aircraft was on hand or if large, expert repair crews were employed. Stand-by crewmembers stationed at airports might prevent delays caused by unanticipated employee absences. Adopting such measures would add substantial costs; airlines' willingness to incur these costs to improve quality ought to differ based on the extent to which delayed flights cost the airlines in the long run. In fact, current on-time performance by airlines may well be at the profit-maximizing level.

An airline's costs associated with delayed flights will likely depend on its market structure. If the voices clamoring for reduced delays are correct, expected on-time performance is a key non-pecuniary component of an air traveler's utility function. Such a consumer would compare prices and expected on-time performance of the competing carriers on the route for which he or she was buying a ticket. To the extent that consumers' expectation of future delays are based on a carrier's past on-time performance on that route, one potential cost of flight delays for airlines is reduction in future demand. However, since the demand for air travel is quite inelastic for many consumers, the reduction in utility would represent higher costs for the airline when consumers have other carriers as a potential alternative on the route they are planning to fly. If an airline is the only carrier serving a particular route, the future revenue implication of delayed flights would be less severe. Having additional competition should provide incentives for the profit-

[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 strong connection between delayed flights and customers filing complaints on those flights.

maximizing airline to invest in delay prevention, since the cost of delays are greater when consumers have additional options.[4]

A recent paper by Suzuki (2000) suggests how an airline's on-time performance could affect future market share in competitive markets. In the same spirit as I describe above, consumers in Suzuki's model incorporate past flight delays in their choice of carrier. As a result, passengers' propensity to switch airlines increases if they have experienced prior flight 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 past on-time performance. This sort of evidence supports the conjecture that the consequences of poor on-time performance can be substantial in competitive markets.[5]

The data presented in the following section demonstrates considerable variety in the competitiveness of the individual routes that each airline serves. By the argument sketched above, airlines incur a greater cost associated with delayed flights on routes where other firms also offer service, all else equal. In order to maximize firm-wide profits, therefore, airlines may allocate resources so that better on-time performance is generated on their more competitive routes. In many cases, the production inputs are sufficiently fungible to accommodate quick reactions to schedule disruptions. For example, American Airlines flies the same type of aircraft on its routes from Dallas to Nashville and Dallas to Indianapolis. If the Dallas pre-flight maintenance check on the plane planned for Nashville (where Delta also flies from Dallas) indicates a problem that will take an hour to fix, the plane planned for Indianapolis (no competitors) could be substituted. Likewise, a flight attendant could be pulled from the plane bound for Indianapolis if a crewmember on the Nashville flight called in sick. With advanced planning additional resource deployments are possible – aircraft closer to their next scheduled maintenance could be disproportionately assigned to noncompetitive routes, for example. Advances in technology

[4] A considerable theoretical literature analyses the connection between market structure and product quality more formally. Swan (1970) argued that quality (durability) choice was independent of market structure; however, subsequent authors reversed this result by relaxing some restrictive assumptions. For example, Spence (1975) finds that a price regulated monopolist would underprovide quality. Costs matter as well – if the cost of providing additional quality increases slower than demand increases with higher quality, a profit-maximizing monopolist would provide the highest possible quality level. Schmalensee's (1979) review of this literature highlights the situations in which market concentration would lower product quality, but also concludes that "there is an obvious need for empirical work to confront the implications of the theoretical literature with data."

[5] Since flight-level price data are not available, there is no effort made in this paper to estimate consumers' willingness-to-pay for on-time performance in a serious way. Instead, by comparing quality outcomes across markets, I hope to generate some evidence to suggest that competitive forces provide an incentive for firms to provide additional quality to consumers.

used by airlines to support operations have made this sort of profitability-enhancing input manipulation much easier in recent years.[6]

In the empirical work, I will examine whether there are within-airline differences in on-time performance that are correlated with the competitiveness of individual routes. While not as widespread as the literature on competition and prices, several empirical papers examine the connection between quality provision and market concentration.[7] For example, Hoxby (2000) finds that metropolitan areas with more school districts have higher quality in terms of greater student achievement levels. 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. In the airline industry, an early study by Douglas and Miller (1974) investigates flight frequency as the measure of quality across city pair markets. Borenstein and Netz (1999) examine the connection between market competition and the times when flights are scheduled. Mayer and Sinai (2002) perform an extensive empirical evaluation of on-time performance, focusing on the effects of congestion on flight delays and the externalities imposed by certain patterns of flight scheduling. Finally, Foreman and Shea (1999) find evidence that average delays decreased after the airlines were required to publish on-time performance rates. They also find a positive correlation between on-time performance and competition, but their competition measure is very crude.[8]

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 – for each flight number to consumers along with details

[6] McCartney (2000) reports on systems used by Continental Airlines to allocate staff at hubs, organize crew schedules and overnight maintenance, and even adjust meal quality based on passenger load.

[7] Sutton (1991) discusses how firms' exogenous investments to promote consumer willingness-to-pay can ultimately lead to market concentration. As of now, there is no evidence that relatively poor on-time performance has driven any firm out of a particular city-pair market. The maintained assumption here is that airlines take route structure as exogenous and fixed when deciding on their investments to provide quality service.

[8] The empirical work analyzes the effects of actual competitors only. Theoretically, airline markets could be contestable if sunk costs are low enough – thus, potential entrants would discipline monopolists to provide better on-time service. Though contestability was an early motivation for deregulating the airline industry, subsequent analyses (e.g., Morrison and Winston, 1987; Peteraf, 1994) have found empirical evidence incompatible with contestability in terms of fares. To the extent that the results for quality are similar, this paper may provide further evidence that the airline industry is not contestable.

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 the extensive compendium of information on which these averages are based. The BTS’s Office of Airline Information tracks the entire domestic system of the (then) ten major U.S. airlines (Alaska, America West, American, Continental, Delta, Northwest, Southwest, TWA, United and USAir).[9] 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 list of airports, and the number of flights in the dataset taking off and landing from each, is presented in Table I. Over 800,000 individual flight observations are included in the dataset.[10]

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 from the BTS 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 a substantial portion of the flights recorded were “early” – 9.7 percent of flights reached their gate prior to the scheduled arrival time. This does suggest that a certain amount of slack may be built into the airlines’ schedules; I 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 in addition to the industry’s definition of “late.”

To isolate the effect of market structure on on-time performance, it is necessary to control for factors that affect the ability to adhere to schedule, but which carriers have less ability to manage. 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

[9] The data collected for this paper are from a period prior to the bankruptcy of TWA and its subsequent takeover by American. Therefore, TWA remains in the analysis here.

[10] The data are maintained in a searchable database at http://199.79.179.77/ntda/oai/ DetailedStatistics. Note that the BTS maintains a separate file for flights that are cancelled. Cancelled flights clearly make consumers worse off; however, it is difficult to integrate them into the analysis without making *ad hoc* assumptions regarding their comparability. Therefore, only completed flights are included in this analysis.

Table I. 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%
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%

Table I. Continued

Airport	Outbound flights	Inbound flights	Share of total flights by carrier									
			Alaska	Am. West	American	Continental	Delta	Northwest	Southwest	TWA	United	US Air
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%

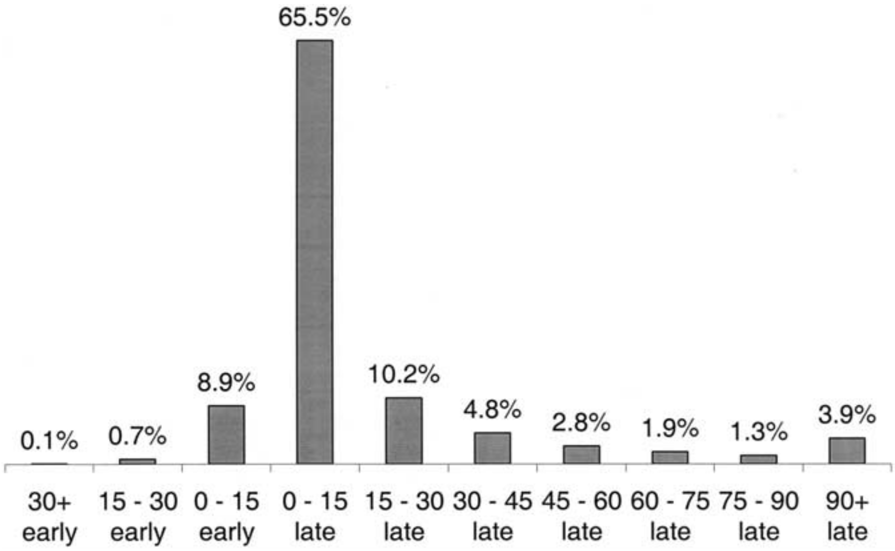

Figure 1. Histogram of "minutes late" in the dataset.

throughout the country that is also accessible through the Internet.[11] 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. Table II provides definitions and summary statistics for all the variables used in the empirical analysis.

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 congestion 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 their congestion levels at different times of the day.[12] 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 also include airport fixed effects in the regressions to control for capacity and other airport-specific factors that I cannot measure directly.

[11] The NWS archived data are located at http://nndc.noaa.gov/?http://ols.ncdc.noaa.gov/cgi-bin/nndc/buyOL-002.cgi.

[12] Mayer and Sinai (2002) attribute the differential performance of hub airlines and other operating at hubs to scheduling differences – to achieve network benefits, hub airline flights are necessarily scheduled at congested times. By counting the actual number of flights scheduled to land each hour, I can control for this more directly.

Table II. Variable definitions and summary statistics

Variable	Definition	Mean	Std. dev.
Weather conditions			
COLD	Dummy Variable = 1 if origin or destination airport reported temp. below 30 on day of flight	0.408	0.49
THUNDER	Dummy Variable = 1 if origin or destination airport reported thunderstorms on day of flight	0.172	0.38
RAIN	Dummy Variable = 1 if origin or destination airport reported rain on day of flight	0.192	0.39
SNOW	Dummy Variable = 1 if origin or destination airport reported snow on day of flight	0.105	0.31
FOG	Dummy Variable = 1 if origin or destination airport reported fog on day of flight	0.657	0.48
HAZE	Dummy Variable = 1 if origin or destination airport reported haze on day of flight	0.462	0.50
Flight, airport & airplane characteristics			
ARR_TIME	Scheduled arrival time of flight (0 = 12:01 am; 1 = midnight)	0.637	0.21
MILES	Length of flight in miles	872.7	609.2
TOEAST	Compass direction of flight, 1 = E; −1 = W	−9.11e-6	0.73
INTOHUB	Dummy Variable = 1 if destination is a hub for that carrier (list of hub/airline combination in footnote 18)	0.415	0.49
OUTOFHUB	Dummy Variable = 1 if origin is a hub for that carrier (list of hub/airline combination in footnote 18)	0.433	0.50
CONGEST	Number of flights scheduled to land in the same hour at the destination airport of the flight	22.75	15.08
AGE	Age of aircraft used for flight	14.13	10.14
NO_SEATS	Number of seats on aircraft used for flight	151.90	70.31
AIRBUS	Dummy Variable = 1 if aircraft used on flight was manufactured by Airbus	0.83	0.28
BOEING	Dummy Variable = 1 if aircraft used on flight was manufactured by Boeing	0.481	0.50
Concentration measures			
SOLO	Dummy Variable = 1 if only 1 airline serves the city-pair market Non-stop	0.377	0.49
HHI	Hershman–Herfindahl Index for all carriers offering service between origin and destination airports (revenue-weighted market shares, non-stop and multi-segment)	0.505	0.18
APT_SHARE	Airline's share of total flights at origin airport + airline's share of total flights at destination airport	0.753	0.27
SUBAVAIL	SOLO*OUTOFHUB	0.180	0.38

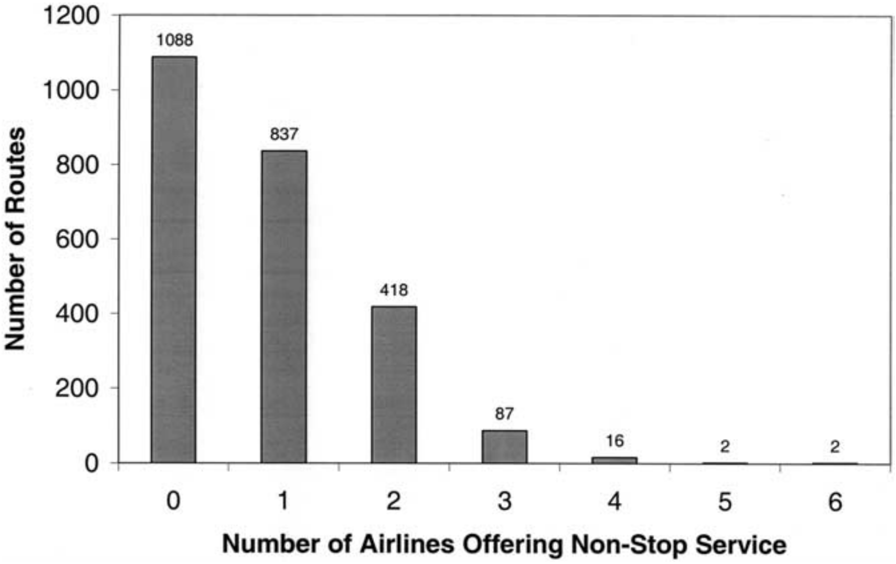

Figure 2. Direct competition in airport-pair routes.

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).[13] 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 permits investigation of 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.

To evaluate the main hypothesis that carriers keep to their schedules less closely in more concentrated markets, I created several alternate measures of competition. 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. There is considerable variety in the degree of direct competition across the markets, as displayed in Figure 2. 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 non-stop 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.

[13] The FAA database is located at www.landings.com/_landings/pages/search/search_nnr.html.

Analysts have also found that indirect service can be a relevant substitute for nonstop service between cities. For example, Reiss and Spiller (1989) find that airlines providing indirect service do have a competitive effect on firms offering non-stop service between two cities. To incorporate this substitute into a measure of concentration, I computed a Hirschman–Herfindahl Index for all service between each pair of airports in the dataset. The U.S. Department of Transportation maintains data on carrier revenue by airport pair that includes multiple segment itineraries as well as non-stop flights.[14] The variable HHI represents the concentration index using airport-pair carrier revenues for 2000. Using revenue-weighted market shares is particularly useful in this context, since the extent to which connecting service constitutes competition to an airline that provides non-stop service will vary across markets depending on the distance between airports and the schedules available to make the necessary connections.

Finally, I 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 I, 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. The empirical model evaluates various measures of on-time performance as a function of (1) weather conditions; (2) flight, airport and airplane characteristics; and (3) concentration. Table III displays the OLS regressions in which "Minutes Late" is the dependent variable. Table IV examines alternative dependent variables, including probits predicting whether a flight is 15 and 45 or more minutes late and RELLATE, which is defined as the minutes late for the flight divided by the average minutes late for all flights into that airport during the same time period.[15] For each estimation, the unit of observation is an individual flight. It is important to note that these estimations include airport and carrier fixed effects; the estimated parameters indicate a particular variable's effect on flight delays after

[14] The data are on the website of the DOT's Office of the Assistant Secretary for Aviation & International Affairs, and can be found at http://ostpxweb.dot.gov/aviation/aptcomp/aptcomp2000.htm.

[15] I divided each day into four six-hour blocks to calculate the average minutes late for comparison purposes. This dependent variable gives an alternate method for controlling for effects other than concentration. I thank one of the referees for suggesting this specification.

controlling for unobserved factors at each airport and for each airline's average on-time performance.[16]

As expected, the weather variables are very significant predictors of on-time performance. 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 arriving later than its scheduled time. The delay is particularly long – more than 12 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.

The remaining flight-specific variables reflect additional characteristics that may affect on-time performance. The variable ARR_TIME indicates the scheduled arrival time of each flight, with the 24-hour day converted to a scale from zero to one. The estimated effect of arrival time is very large: the average flight arriving at 8 pm is about 9 minutes more behind schedule than flights arriving at 8 am. The variable MILES represents the flight's distance and TOEAST its 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 parameter estimates on both of these variables are negative and significant, suggesting that it may be possible to "make time up in the air" on longer flights or when wind conditions are favorable. The coefficient on CONGEST is positive and significant, indicating that flight delays are greater when the number of flights scheduled to land in a given hour is higher. Controlling for these factors, an airline's performance at its own hub is better than average. In particular, the INTOHUB variable is negative and significant.[17] Hub carriers have a greater incentive to keep connecting passengers from missing flights, as the costs to rebook passengers onto new connections and to monitor interrupted baggage are substantial. In addition, a passenger's delay – and frustration – may be compounded if delays cause a connecting flight to be missed. Interestingly, the OUTOFHUB dummy has a much smaller effect, particularly for determining whether a flight is more than 15 or 45 minutes late.

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[16] The estimated airline fixed effects roughly correlate with average on-time performance for the airlines as reported by Bowen and Headley (2001), and the estimated airport fixed effects are also as expected. Dummy variables were also included for each month's data – delays were much greater in July than in January or April. This may indicate that delays are getting worse over time, but with only one year's data some other seasonal variation cannot be ruled out. Day of the week controls indicated that flights were more likely to be on-time on light travel days (Tuesday and Saturday), while Friday flights had significantly longer delays. These results are not reported in Tables II and III, but are available from the author on request.

[17] INTOHUB is a dummy variable whose value is one if the flight's destination is one of the airline's major hubs *and* if the carrier on the flight is the airline whose hub is in that city. Therefore, INTOHUB equals one for 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, San Francisco; US Air/Charlotte, Philadelphia, Pittsburgh. The OUTOFHUB dummy is one for flights originating in hubs – with the same list of carrier/origin pairs.

Table III. OLS Regressions of airline delay length (flight-level regressions – number of observations = 769,782; dependent variable: minutes late (time between scheduled and actual gate arrival) mean = 10.7 minutes)

	Panel 1 – base regression			Panel 2 – alternate concentration variable			Panel 3 – base regression including SUBAVAIL		
	Coeff.	Std. err.	t-stat.	Coeff.	Std. err.	t-stat.	Coeff.	Std. err.	t-stat.
CONSTANT	−9.478	0.516	−18.36	−11.037	0.545	−20.203	−9.324	0.517	−18.03
COLD	−3.778	0.133	−28.34	−3.773	0.133	−28.23	−3.781	0.133	−28.35
THUNDER	12.631	0.128	98.95	12.639	0.128	98.77	12.631	0.128	98.95
RAIN	6.309	0.121	52.07	6.319	0.121	52.04	6.309	0.121	52.08
SNOW	8.636	0.158	54.76	8.627	0.158	54.57	8.638	0.158	54.77
FOG	2.319	0.113	20.50	2.349	0.113	20.71	2.318	0.113	20.49
HAZE	−0.192	0.098	−1.95	−0.189	0.099	−1.92	−0.191	0.098	−1.94
ARR_TIME	18.590	0.196	94.96	18.607	0.196	94.82	18.556	0.196	94.72
MILES (00s)	−0.077	0.008	−9.21	−2.9e-4	8.8e-5	−3.30	−0.076	0.008	−9.14
TOEAST	−1.213	0.057	−21.32	−1.216	0.057	−21.32	−1.222	0.057	−21.46
INTOHUB	−3.746	0.211	−17.74	−3.745	0.212	−17.69	−3.681	0.212	−17.39
OUTOFHUB	−1.150	0.210	−5.48	−1.130	0.210	−5.38	−1.401	0.217	−6.47
CONGEST	0.029	0.004	8.27	0.030	0.004	8.48	0.030	0.004	8.53
APT. SHARE	4.387	0.355	12.36	3.974	0.368	10.79	4.257	0.356	11.96
SOLO	1.353	0.131	10.35	–	–	–	0.977	0.153	6.37
HHI	–	–	–	3.96	0.398	9.95	–	–	–
SUBAVAIL	–	–	–	–	–	–	0.830	0.177	4.68
Adjusted R^2		0.073			0.074			0.074	

Fixed-effect dummy variables for each month, day of the week, airport and carrier were also included in these regressions.

Table IV. Airline delay analyses – alternate dependent variables (flight-level regressions – number of observations = 769,782

	Panel 1 – probit Dep. var. = I(min. late > 15)			Panel 2 – probit Dep. var. = I(min. late > 45)			Panel 3 – OLS regression Dep. var. = RELLATE		
	Coeff.	Std. err.	z	Coeff.	Std. err.	z	Coeff.	Std. err.	t-stat.
CONSTANT	−1.569	0.020	−78.48	−2.373	0.027	−89.16	−8.375	0.515	−16.25
COLD	−0.120	0.005	−22.75	−0.175	0.007	−25.20	−3.763	0.133	−28.27
THUNDER	0.371	0.005	76.92	0.449	0.006	75.85	12.649	0.127	99.24
RAIN	0.249	0.005	53.89	0.269	0.006	46.08	6.290	0.121	52.04
SNOW	0.319	0.006	53.14	0.341	0.008	44.46	8.731	0.157	55.45
FOG	0.098	0.004	21.87	0.103	0.006	17.57	2.306	0.113	20.41
HAZE	−0.021	0.004	−5.41	−0.004	0.005	−0.91	−0.170	0.098	7.73
ARR_TIME	0.764	0.008	99.12	0.929	0.010	92.16	1.543	0.195	7.90
MILES (00s)	0.005	0.000	17.34	−0.002	0.000	−4.84	0.001	8.30e-5	−13.02
TOEAST	−0.061	0.002	−27.87	−0.037	0.003	−13.12	−1.156	0.568	−20.25
INTOHUB	−0.154	0.008	−19.19	−0.131	0.010	−12.99	−2.831	0.211	−13.43
OUTOFHUB	0.016	0.008	2.04	−0.001	0.010	−0.05	−1.042	0.209	−4.97
CONGEST	0.002	0.001	11.70	0.001	0.000	5.44	0.005	0.004	1.48
APT. SHARE	0.159	0.014	11.58	0.046	0.017	2.61	3.048	0.354	8.60
SOLO	0.061	0.005	11.94	0.061	0.007	9.43	1.442	0.131	11.05
Pseudo-R^2/R^2		0.065			0.085			0.049	

Fixed-effect dummy variables for each month, day of the week, airport and carrier were also included in these probits.

The remaining rows of Tables III and IV contain the key variables of interest in evaluating the hypothesis that airlines have worse on-time performance on their least competitive routes. The estimates here provide empirical support for this hypothesis, as the SOLO dummy (equals one if there is only one carrier flying direct on the route), the HHI measure (including both nonstop and connecting service), and the APT_SHARE variable (percent of flights from the origin and destination airports the carrier represents) are positive and significant in the minutes late regression and the late flight probits. Note that these effects may come from somewhat different sources. SOLO and HHI capture direct effects that may influence fliers who commonly take a particular route. APT_SHARE reflects airports where frequent fliers have less choice among all the places they intend to fly.[18] In the third panel of Table III, I split up the SOLO variable by including an interaction between the SOLO and OUTOFHUB dummy variables. This new variable, SUBAVAIL, represents flights whose equipment or crew could easily be borrowed by a flight on competitive route at the same hub, if needed. The effect is incremental, and the coefficient estimate is positive and significant. While delays are significantly greater on the less competitive routes, the effect appears to be more acute at airports where competitive routes also originate. This suggests that airlines may be organizing their production inputs with the competitiveness of their routes in mind.

Table V reproduces the base "minutes late" regression with the airplane characteristic variables collected from the FAA added. Here, I have included the age of the aircraft on each flight, the maximum number of seats that can be configured in the aircraft, and dummy variables for aircraft manufactured by BOEING and AIRBUS.[19] Not surprisingly, the older planes arrive at their destination later than planned more often. In addition, AIRBUS planes are about 1.6 minutes later than planes manufactured by other firms, on average. The NO_SEATS coefficient is positive and significant, even though more passengers are potentially inconvenienced if a larger plane is delayed. Of course, NO_SEATS does not reflect the actual number of passengers on each flight. The airlines know precise loads on individual flights and may well take actions to maintain better service when a larger number of customers are involved. Finally, no evidence was found to suggest that aircraft with characteristics that predicted flight delays were disproportionately deployed on non-competitive routes.

Table VI presents a regression whose dependent variable is the scheduled elapsed time for each flight in the dataset. Airlines have been criticized for "pad-

[18] The magnitude of the effects can also be determined from these results. A flight on a monopoly route is on average 1.35 minutes later than a similar flight on a competitive route, and if the carrier has 22% greater origin or destination market share the average delay on the flight increases by one minute. Computing derivatives using the estimates from Table IV indicates that a particular flight is between 1 and 2 percent more likely to be late if it is operated by the only carrier that flies between the two cities.

[19] The excluded category includes equipment manufactured by firms such as Fokker and McDonell-Douglas.

Table V. Minutes late regression including aircraft characteristics flight-level regressions – number of observations = 769,782; dependent variable: minutes late (time between scheduled and actual gate arrival) mean = 11.4 minutes

	Coeff.	Std. err.	t-stat.	*p*-value
CONSTANT	−12.359	0.597	−20.71	0.000
COLD	−4.092	0.150	−27.24	0.000
THUNDER	13.768	0.143	96.11	0.000
RAIN	6.969	0.135	51.51	0.000
SNOW	10.068	0.176	57.17	0.000
FOG	2.104	0.127	16.55	0.000
HAZE	−0.246	0.110	−2.23	0.026
ARR_TIME	19.058	0.218	87.28	0.000
MILES (00s)	−0.085	0.010	−8.70	0.000
TOEAST	−1.375	0.064	−21.54	0.000
INTOHUB	−3.913	0.252	−15.50	0.000
OUTOFHUB	−1.164	0.252	−4.63	0.000
CONGEST	0.026	0.004	6.66	0.000
APT. SHARE	5.010	0.441	11.36	0.000
SOLO	1.458	0.147	9.89	0.000
AGE	0.180	0.008	22.62	0.000
NO_SEATS	0.007	0.001	6.00	0.000
AIRBUS	1.647	0.229	7.19	0.000
BOEING	0.272	0.128	2.12	0.034

Fixed-effect dummy variables for each month, day of the week, airport and carrier were also included in these regressions.

ding" their schedules to avoid missing their scheduled arrival times; this could potentially bias the results from Tables III and IV. Of course, scheduled time is prescribed mostly by the flight's distance and direction. 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 reflect the logistical difficulties associated with turning around large banks of flights at busy hub airports.

There are mixed results for the concentration variables in the scheduling regression. SOLO flight schedules appear to be padded; as a result, the SOLO coefficient may be biased downward in the on-time estimations. This may also reflect consumers' preference for reaching their destination more quickly – airlines respond with a more accurate schedule on routes where consumers have more than one option. 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

Table VI. OLS regression of airline flight scheduling (flight-level regressions – number of observations = 769,782; dependent variable: scheduled duration of each flight; mean = 144.4 minutes)

	Coeff.	Std. err.	t-stat.	*p*-value
Constant	31.819	0.114	278.18	0.000
APRIL	−0.774	0.024	−32.28	0.000
JULY	−1.973	0.024	−83.22	0.000
MONDAY	−0.106	0.034	−3.13	0.002
TUESDAY	−0.084	0.035	−2.38	0.017
WEDNESDAY	−0.120	0.035	−3.43	0.001
THURSDAY	−0.127	0.035	−3.61	0.000
FRIDAY	−0.134	0.035	−3.82	0.000
SATURDAY	0.292	0.034	8.52	0.000
Miles	0.118	0.000	6170.61	0.000
"To East"	−10.271	0.013	−782.66	0.000
ARR_TIME	5.223	0.045	115.73	0.000
INTOHUB	−0.342	0.049	−7.02	0.000
OUTOFHUB	1.239	0.048	25.63	0.000
CONGEST	0.116	0.001	142.54	0.000
APT. SHARE	−0.862	0.081	−10.54	0.000
SOLO	0.195	0.030	6.47	0.000
Adjusted R^2		0.9874		

Fixed-effect dummy variables for each airport and carrier were also included in this regression.

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; this may be reflected in scheduling.

Figure 3 displays the estimated carrier fixed effects from the on-time and scheduling regressions along side the raw average minutes late for each carrier in the dataset. The fixed-effect estimates from the minutes late regressions follow the raw averages reasonably closely. It does appear, however, that some airlines benefit from selection effects in keeping to their schedules. For example, the average flight on American is nearly four minutes later than the average flight on Northwest, but their estimated carrier fixed effects are almost identical. Although a substantial portion of United's poor performance in 2000 was carrier-specific, it appears that their flights were particularly susceptible to weather, congestion, and airport-related delays.[20] The carrier fixed effects from the scheduled elapsed time

[20] United's average minutes late is 5.7 minutes greater than the next worst performer (America West) and 14.0 minutes more than the best (Northwest) carrier's average delay. However, United's

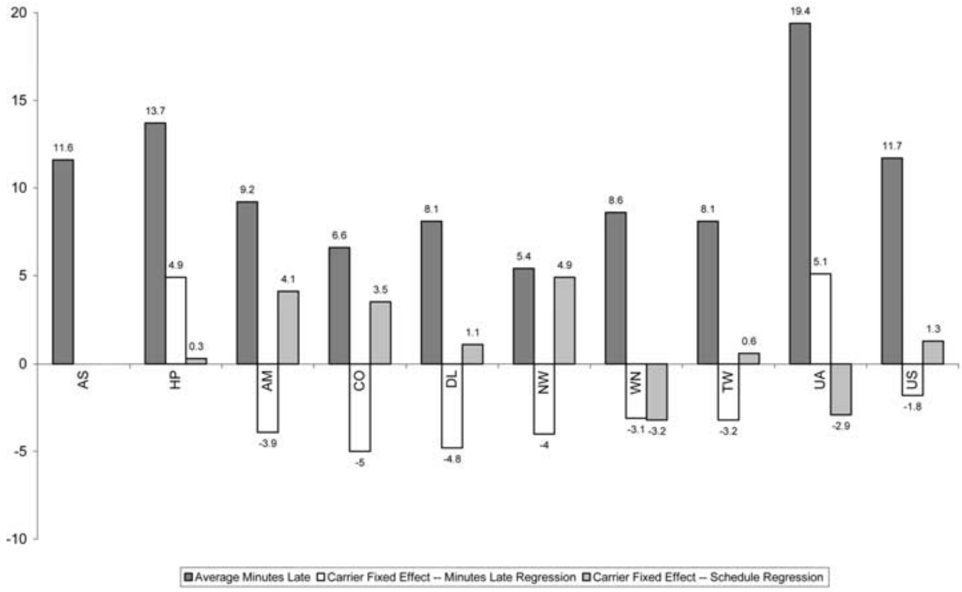

Figure 3. Carrier fixed effects on delays and schedules

regression suggest that some airlines' relatively good on-time performance may result from allowing more time on similar flights rather than from getting passengers to their destination more quickly. Among the five airlines with the lowest fixed effects estimates in the minutes late regression, three (American, Continental and Northwest) have the largest estimated fixed effects in the scheduled elapsed time regressions. This at least partially offsets the quality of these airlines' service, although consumers likely receive utility from being on-time as well as from getting to their destination quickly. Southwest is notable for having estimated carrier fixed effects that are negative and significant in both regressions. It also appears that United has set itself up to be delayed more often by scheduling a shorter amount of time for its flights.

The results in this section reveal factors that explain the on-time performance of flights. Weather, congestion and carrier/airport fixed effects are significant predictors of whether a flight arrives at its destination on time and how long delays last. Controlling for these factors helps to isolate the effects of market concentration – flights on routes with no direct competition have significantly longer schedule times and significantly longer delays. When comparing on-time performance of airlines in the aggregate, it is crucial to account for route selection effects, as the difference between the minutes late averages and the carrier fixed effects estimates suggests.

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estimated carrier fixed effect was only 0.2 minutes greater than the next worst (America West) and only 10.1 higher than the lowest carrier fixed effect (Continental). Note that Alaska is the excluded carrier in both the on-time and the scheduled time regressions.

It is important to reiterate two caveats to the results presented above. First, without incorporating data on demand it is difficult to make a reliable welfare statement about the relationship between quality and market structure. The analysis here cannot rule out the possibility that worse on-time performance in monopoly markets disproportionately affect consumers who value time less and are willing to trade delays for lower prices. I collected data on the per capita income of the MSAs associated with each airport – variation in the origin/destination income had no explanatory power in the minutes-late regression. Unfortunately, price data were not available to match with this flight-level on-time dataset; however, none of the many other studies of market concentration and airline fares suggest a negative correlation between monopoly routes and fares.[21]

Finally, recall that the results presented on the connection between market structure and on-time performance are conditional on the schedules the airlines have established. To the extent that there is some unobserved factor explaining delays on particular routes that is correlated with the propensity for airlines to offer service on that route, the effects of market structure on performance may be biased. While some delay-prone routes may be monopolies rather than duopolies, others might not attract any direct service, making it difficult to sign the potential bias. A model that predicts the market structure of city-pair routes, as well as on-time performance, may be a valuable extension to further examine these striking correlations.

V. Conclusion

With several mergers being proposed or considered and increasing calls for government intervention to address on-time performance, competition policy analysis is at the forefront in the U.S. airline industry. Unlike previous studies that focus on prices, this paper examines the hypothesis that the market power which dominant carriers enjoy allows them to provide a lower quality of service – through increased flight delays – to their customers on less competitive routes. 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.

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

[21] See, for example, Borenstein (1989), Hurdle et al. (1989), Morrison and Winston (1990), etc. Even studies like Evans and Kossides (1994) that fail to find a significant positive correlation between concentration and fares do not suggest that the correlation is negative.

standards. Welfare analysis ought to address how firms' incentives to provide quality vary with different levels of market concentration and how consumers value higher or lower quality services. For airlines, an extension that estimates demand for air travel as a function of prices and on-time performance would be a useful exercise. This may provide a better understanding of the economic forces airlines face when making and adhering to their schedules and the potential connection between market structure regulation and the provision of quality service for the public.

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