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Determinants of fares and operating revenues at US airports ☆

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Abstract

This paper investigates the effects of market structure on prices that airlines charge to passengers and, in particular, on revenues that airports obtain from airlines and passengers. The estimated effects of market structure on airline fares are similar to earlier findings, and the results of the passenger, airline demand, and delay equations are as expected. Airports' aeronautical and concession charges are related to market structure, but the relations are less straightforward than in the case of fares, especially regarding the vertical relations between airports and airlines. The results on aeronautical charges are consistent with the practice of charging on the basis of airplane weight.

JEL classification: R41; L93

Keywords: Airports; Airlines; Pricing

1. Introduction

Air travel requires airline and airport services. Airline pricing is the subject of an extensive econometric literature, but much less empirical work has been done on airport pricing. This paper investigates the determinants of airport charges in the US, using an econometric model that is inspired by literature on the economics of airport pricing.

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Large US airports are publicly owned,[1] and provide services for commercial aviation (large carriers, air taxis and commuters) and for general and military aviation. Here, we restrict attention to commercial aviation, which generates most revenues and represents the majority of output at large airports [25]. Airports make revenues from aeronautical services (mainly landing fees and terminal rents) but also, and to a large and increasing extent, from concessionary services like retail shops, parking and rental car service. The main goal of this paper is to investigate the dependence of average aeronautical charges per flight and of average concession charges per passenger, on the market environment in which airports operate. But since airports provide intermediary services, which are used by passengers and by airlines, the regression equations explaining the airport charges are embedded in a system of equations where average fares, demand for travel and for flights, and average delays, are endogenous variables in addition to aeronautical charges and concession charges. Each of these endogenous variables is defined at the level of an airport. The market characteristics are exogenous, and include determinants of demand as well as indicators of vertical relations between airlines and airports and of potential competition between airports.

While airlines have gone through several periods of turmoil since deregulation in 1978, airports' financial performance has been more stable. One reason may be that passengers traveling between city pairs are likely to have a choice of airlines, while airlines' choice of airports connecting the city pair is usually limited. Another explanation may be that long run contracts between airlines and airports have partly shielded airports from revenue risk related to fluctuating demand. It has indeed been the business model of many large airports to rely on revenue generated by one or a few large carriers, and to let airlines assume financial risk. In return the airport gives up some control, with some cases where an airline effectively controls the airport (possibly including decisions on capacity expansion, through "majority in interest clauses" as well as access to current capacity).

There are indications that the control of airports by airlines is diminishing: the share of exclusive use gates at large airports is declining [13], and "hub premiums" are declining [5]. This could occur because airport authorities seek more independence, through the adoption of more flexible agreements between carriers and airports.[2] Other reasons are the rising market share of low cost carriers, because of which legacy carriers' hub airports face more uncertainty, and the increased use of regional jets instead of mainline jets, leading to more aircraft operations for the same amount of passengers.[3] These changes have been underway since the 1990s, but were intensified by the demand shock of 2001.[4]

[1] 63.9% of commercial service airports are owned by a local government, the rest by a single purpose authority [13].

[2] Passenger Facility Charges, introduced in 1990, were designed to provide airports with a source funds for infrastructure expansion that is not airline specific. Hartmann [15] finds that increased flexibility in the arrangements between airports and airlines positively affects airlines' probability of offering a non-stop airport connection, keeping service characteristics (including prices) exogenous.

[3] There were 9 regional jets in 1993 and 976 in 2002. While there is overlap in the seating capacity between the categories of regional and mainline jets, regional jets tend to be smaller than mainline jets. The increase in per passenger airport costs associated with the increased use of regional jets may be particularly large when regional jet operations are concentrated in peak hours (as is the case according to [24]), so exacerbating congestion.

[4] The frequent bankruptcies of large carriers render reliance on a small number of large carriers especially risky. US Airways, for example, rejected all its leases and agreements at Pittsburgh Intl. airport, effective January 5 2004, just before its emergence from Chapter 11 [23]. In April 2006, Delta Airlines rejected some leases and agreements regarding facilities at Cincinnati Airport, also as part of a Chapter 11 restructuring process (http://news.delta.com/print_doc.cfm?article_id=10196).

Recent theoretical work on airports analyzes price and capacity decisions under various assumptions on market structure, focusing on the fact that airports are congestion-prone, and assuming that airports are independent from airlines. Zhang and Zhang [26] focus on vertical interactions between oligopolistic airlines and one airport, assuming that airports maximize local welfare, revenues, or profits, taking market structure and market demand as given. De Borger and Van Dender [10] focus on airports that compete with other airports, as is likely to be the case in multi-airport regions. Zhang and Zhang [26] emphasize that understanding airport behavior requires taking explicit account of the two main revenue sources, aeronautical services and concession services. While there is no exact match between our empirical model and any of these contributions, they do inspire the econometric specification. The econometric model consists six simultaneous equations, three of which capture pricing behavior (fares, aeronautical charges, and concession charges), two that refer to demand (for trips and for flights), and one that models airport delays.

Our findings concerning the impact of market structure and of network features on airline fares are in line with earlier work. For example, average fares are lower at airports dominated by Southwest Airlines, and they are higher at hub airports. The results of the passenger and flight demand equations are as expected. The delay equation produces reasonable results, although the finding that hub airports exhibit shorter delays while airline concentration increases delays, runs counter to earlier work on the topic. We hypothesize that hub and concentration effects may be confounded in our analysis, because of the high level of aggregation.

With respect to average aeronautical charges, we find a negative effect of departures, possibly because the total charges contain a fixed component. Aeronautical charges are lower at airports that (potentially) compete with nearby airports. The charges increase with airline concentration at the airport, except when Southwest is the biggest airline at the airport. The former may be a consequence of strong vertical ties between airlines and airports, but it could also be the case that oligopolistic interaction between few airlines results in high airport revenues. The latter could be seen as the Southwest effect on airport revenues. Average aeronautical charges are higher at airports with large shares of international departures, at slot-constrained airports, and at airports with long average flight distances. As these variables tend to increase airplane size, the findings are consistent with weight-based charging practices.

Like average aeronautical charges, average concession revenues per passenger decline with volumes. Concession revenues per departing passenger are lower at hubs, probably because of a high share of connecting passengers, who do not consume rental car and parking services. More concentrated airports make less concession revenue per passenger, possibly because vertical relations imply that a bigger share of such revenues accrues to airlines. However, since average concession revenues decline with concentration and average aeronautical revenues increase with concentration, a composition effect may be involved as well.

Overall, our results indicate that market structure affects airport charges, but they are also consistent with aeronautical charges that are based on airplane weight. So, while market structure matters, the structure of the charges is different from what is predicted by models that view airports as congestible facilities with market power, while it is in line with available descriptions of airport charging practices. Such descriptions strongly suggest that airport charges are at least partly determined by other factors than those considered in the theoretical models, because of a tradition of average rather than marginal cost-based pricing, but also because of contractual arrangements between airlines and airports [1,9,12,13].

The findings that average concession revenues decline, and average aeronautical revenues increase with airline concentration at the airport, are not readily explained on the basis of theory on airport pricing, nor by referring to weight-based charging systems. There may be at least two reasons for this. First, measurement problems concerning airport charges may produce misleading results. Second, the empirical results are accurate, but the theory on airport pricing misses important features of airport behavior, in particular characteristics of vertical relations between airlines and airports.

If the latter is true, there could be reasons for airports to deviate from the pricing practices that private congestible facilities with market power should adopt according to theory (which does not in itself imply that the current system is optimal). The question is relevant, as it concerns the possible consequences of increased "commercialization" of airports: will future airport prices correspond more closely to what theory suggests, and hence be very different in level and structure from what is currently observed, or are there elements in the vertical relations between airlines and airports that may inhibit change? We briefly return to the issue in the conclusion.

The remainder of the paper is structured as follows. Section two discusses data and the econometric implementation. Section three discusses results, and section four offers concluding remarks.

2. Data and econometric model

This section begins by highlighting features of the data set that facilitate the interpretation of the estimation results; a more detailed description of scope and variables is in Appendix A. Next, we discuss summary statistics and introduce the econometric specification.

Our data set covers 55 large US airports from 1998 through 2002. Across all observations, concession revenue represents slightly more than half of total operating revenue on average, but its share dropped with the slump in travel in 2001 and especially 2002. Aeronautical revenue consists mainly of landing fees and terminal rents (84% combined). Landing charges still are mostly based on aircraft weight,[5] and rental fees are likely to be the subject of long run contracts between carriers and airports, so the response to market shocks may be slow and possibly also limited. Within concession revenue, shares are nearly 25% for revenues from terminal businesses, 20% for revenues from rental car services, and 40% for parking revenues. Variations across airports in the revenue structure are large. This may be related to business strategies (including vertical ties with airlines), to local conditions, or to accounting practices, neither of which are captured in the explanatory data. For this reason, and because accounting conventions for some subcategories changed between 1998 and 2002, the econometric analysis refers to the aggregate revenue sources, aeronautical and concession revenue, where idiosyncratic variation hopefully is less of a problem.

In building the model, we assume that trips and segments are symmetrical, and restrict attention to an airport's role as a trip origin and point of departure for a segment.[6] Variables are defined at the airport-year level. This is a much higher level of aggregation than many earlier studies of the airline industry have used, but more disaggregated data on airport revenues are not readily available.

[5] Cf. the introduction in [9] for an overview of the logic underlying airport charges. While some changes have taken place over time (e.g. the move from residual landing charges to cost-center approaches), the description in [16] still captures many fundamental features of airport charges.

[6] Comparisons of origin- and destination-based regressions with early model versions suggest that the symmetry assumption is reasonable.

The endogenous variables are flight fares, average aeronautical charges per flight, average concession revenues per passenger, demand for passenger departures, demand for flight departures, and airport delays. The explanatory variables capture key features of airports' market environment. Variables like income and population are included because they affect passenger demand for departures from the airport. Other variables, for example airline concentration at the airport and the presence of potential substitute airports, capture elements of vertical relations between airports and airlines and of horizontal relations between airports. We also take account of arrival and departure delays, as indicators of congestion or service quality. Table 1 provides variable labels with a brief explanation, and summary statistics.

It is important to note that explanatory variables are defined in different dimensions, depending on the source they are obtained from. This issue needs to be taken into account when interpreting results. For example, socio-demographic variables are defined for the geographical location of the airport, neglecting the characteristics of destinations that are reached from that airport. But the main shortcoming is that fares, obtained from DB1A data, are defined on the level of a trip from a passenger's origin to her destination, while many other variables (especially those relating to traffic volumes and delays) are taken from T-100, which implies that they are defined at the level of a flight segment. Given the hub-spoke structure of many airlines' networks, passenger trips often consist of more than one segment, so that there is no match between the dimension of passenger fares and the volume measures. More specifically, the fare measure applies to trips for which the airport is a trip origin or a trip destination. It does not capture fares paid by connecting passengers: they use the airport to depart on a flight segment, but the airport is not the origin or the destination of their trip.

The extent of the measurement problem for fares differs among airports, because the shares of local and through traffic differ among them. The latter point can be remedied to some extent by using a fixed effects specification, but we are more interested in the estimation excluding fixed effects (for reasons set out below). One consequence of the differing dimensions is that passengers' response to average airport fares should not be interpreted as a well-defined elasticity. For the fare equation itself, the problem is less serious, as long as the hub status is controlled for. Still, the coefficient of average distance is likely biased, because distance is measured at the segment level, and hence approximates trip distance relatively well at hubs, but not at non-hubs. Given that the main contribution of this paper lies in its attempt to explain airport charges, we opt for defining as many variables as possible in the most relevant dimension for those charges (segments). The fare equation and the role of fares in other equations is included to obtain a more complete representation of the industry, but the precise coefficients here are of lesser interest.

A shortcoming of the T-100 data is that not all regional carriers are included before October 2002. According to Accounting and Reporting Directive 261 issued by the Office of Airline Information of the Bureau of Transportation Statistics,[7] small certificated and commuter air carriers were required to start filing T-100 nonstop segment and on-flight market data as of October 2002. As some regional carriers were reporting before the requirement, only a portion of the regional operators were affected by the directive.[8] For our purposes, the implication of the lack of

[7] http://www.bts.gov/programs/airline_information/accounting_and_reporting_directives/ (accessed on 9/6/2006).

[8] Regional carriers owned by major carriers (American Eagle, Executive Jet, Comair, Atlantic Southeast, Mesaba) are considered as large certificated carriers, and reported before 2002. The Alaskan Air carriers began reporting T-100 data January 2002. All other small certificated and commuter air carriers began reporting T-100 data October 2002 (personal communication with J. Fabrizi, US DOT). Filing requirements for all cargo carriers changed as well, which can be expected to have large effects on measured volumes for Memphis and Louisville airports.

Table 1
Descriptive statistics for the 1998–2002 sample of 55 US airports (275 observations, prices of 2000)

Variable	Brief explanation[a]	Natural units		Units in model			
		Mean		Mean	Std. Dev.	Min	Max
Endogenous variables							
ln_aero_dept	average aeronautical revenue per departing segment	532.510	$	6.278	0.555	4.982	8.221
ln_airportdelay	average total delay at the airport	9.653	minutes	2.267	0.572	−0.989	3.294
ln_airportfare	average price of a ticket on a departing trip	154.960	$	5.043	0.218	4.369	5.492
ln_conc_pass	average concession revenue per departing passenger	7.225	$	1.978	0.386	0.990	3.300
ln_departures	flight segments departing from the airport	80,688	flights	11.298	0.764	9.878	12.948
ln pass	number of passengers departing on segments	6.819.932	passengers	15.735	0.777	14.259	17.498
Exogenous variables							
acluster	airport potentially competes with nearby airports	0.400	dummy	0.400	0.491	0	1
carr_per_dest	ratio of number of carriers and number of destinations at the airport	0.333	index	0.333	0.084	0.155	0.550
D1999	dummy = 1 if year is 1999, 0 otherwise	0.200	dummy	0.200	0.401	0	1
D2000	dummy = 1 if year is 2000, 0 otherwise	0.200	dummy	0.200	0.401	0	1
D2001	dummy = 1 if year is 2001, 0 otherwise	0.200	dummy	0.200	0.401	0	1
D2002	dummy = 1 if year is 2002, 0 otherwise	0.200	dummy	0.200	0.401	0	1
hhi_pass	Herfindahl airline concentration index at the airport	0.283	index	0.283	0.183	0.078	0.961
hub	dummy = 1 if airport is a network hub, 0 otherwise	0.309	dummy	0.309	0.463	0	1
ln_airportdelay*hub[b]	average total delay at hub airports	10.364	minutes	2.338	0.535	1.084	3.241
ln_alldel*acluster[b]	average total delay at airports in clusters	9.874	minutes	2.290	0.602	−0.989	3.259
ln_av_airtime[c]	average segment time out of the airport	2.856	hours	9.238	0.295	8.624	9.977
ln_av_dist	average segment distance out of the airport	705.250	miles	6.559	0.328	5.625	7.622
ln_cap	airport capacity (max. passenger volume 98-02)	7,349,406	passengers	15.810	0.774	14.398	17.498
ln_fare_other	average fare at other airports in same cluster	178.777	$	5.186	0.088	5.04165	5.333
ln_inccap	income per capita in airport's metropolitan area	32,218	$	10.380	0.151	10.005	10.761
ln_pop	population in airport's metropolitan area	3,142,408	inhabitants	14.961	0.982	12.701	16.892
num_dest	number of segment destinations from the airport	123.091	destinations	123.091	60.550	18	277
sh_intl_pass	share of international passengers departing from the airport	0.064	share	0.064	0.109	0	0.553
slotconst	dummy = 1 if airport is slot-constrained, 0 otherwise	0.055	dummy	0.055	0.228	0	1
T-100 dummy	dummy = 1 if large change in T-100 volumes between 1998 and 2005	0.145	dummy	0.145	0.353	0	1

[a] Appendix A describes sources and some variables in more detail.
[b] Summary statistics for hub = 1 or cluster = 1.
[c] Log of seconds.

universal filing by regional carriers before October 2002 means that flight and passenger volumes for 1998–2002 are incorrectly measured, to a degree that depends on regional carriers' market share. Since regional carriers' importance differs among airports, the degree of mis-measurement varies across airports as well. This poses a potentially serious data problem, aggravated by the fact that average airport and airline charges are calculated using T-100 data.

Our treatment of this problem is twofold. First, some airports are eliminated from the analysis, on the grounds that the filing status of regional carriers with a large market share at those airports appears to have changed during the sample period (1998–2002), i.e. before the directive took effect. The airports are Anchorage Intl, Cincinnati Intl, Memphis Intl, Chicago O'Hare, Louisville Intl., and Salt Lake City Intl. Second, we identify airports where traffic volumes reported in T-100 increase exceptionally strongly between 2002 and 2005,[9] with the intention of capturing airports where changes in filing status in response to the directive has a big impact on total traffic volumes at the airport. We introduce a dummy variable which equals one for each of these airports (T-100 dummy), and which equals zero otherwise, to capture the set of airports for which non-reporting during our sample period is likely to cause a large measurement error. Our preferred specification includes this dummy variable. We have also estimated the model after excluding the airports for which the dummy equals one (and dropping the T-100 dummy). Apart from a loss of precision, the results of this estimation are substantially the same as for the preferred specification.

Table 1 shows that the average airport in the sample has 6.8 million passengers that use it as an origin (if all trips are symmetrical roundtrips, there will be 13.6 million passengers per year); airports like Baltimore-Washington Intl., Pittsburgh Intl. and Salt Lake City Intl. are of this average size. The smallest airport is Tucson Intl. airport in Arizona, with 1.5 million departing passengers. The largest one is William B. Hartsfield airport in Atlanta, where 40 million passengers depart per year. The mean ticket price for a trip departing from an airport is the one-way average fare across trip destinations, weighted by passenger volumes; it ranges from \$79 to \$243, with an average of \$155.

Aeronautical revenue and concession revenue per departing passenger both are around \$7.5. Of all airports in the data set, 40% are in a cluster (i.e. there is a potential substitute airport), and 31% function as network hubs (cf. Table A.1 for a list of airports in clusters and hub airports). The concentration index is 28% on average, but ranges from 8 to 96%. Most airport serve mainly domestic travelers. Only John F. Kennedy airport has more international travelers than domestic travelers; at Miami Intl., the distribution is 50/50. The average flight distance out of an airport is 705 miles. Standard deviations for some key variables are large, indicating considerable heterogeneity among airports.[10]

Airports can be classified using several criteria. A particularly useful distinction is that between airports where Southwest or a legacy carrier has the largest market share, as fares and aeronautical revenues are lower at Southwest-dominated airports, while concession revenue is the same. Southwest uses smaller airports with fewer destinations and shorter average segment distances, and the airports serve nearly exclusively domestic passengers; these characteristics suggest that the airports have lower costs, but it could also be the case that Southwest requires fewer services or negotiates lower prices. Only 10% of airports dominated by Southwest are

[9] An exceptionally strong increase is an increase that exceeds the average volume change across 61 large airports by at least one standard deviation. We choose the year 2005 because of large changes in reported volumes in 2003 and 2004, despite the effective date of the filing requirement of October 2002; cf. Appendix A for further detail.

[10] There is more cross-sectional than time-series variation, and the time series variation mainly is the result of common shocks.

hubs, against 60% for airports dominated by a legacy carrier. Both types of airports are similar in terms of delays and concentration.

Alternative airport classifications are possible: hub versus non-hub airports, and medium size versus large airports. In many respects, these groupings are similar to the one based on Southwest vs. legacy carrier dominance, in the sense that many airports dominated by legacy carriers are hub airports and many hub airports are large airports. In contrast, Southwest focuses on smaller non-hub airports.

The following time patterns are noteworthy. Average passenger numbers increase from 1998 to 2000, and drop by more than 600,000, or nearly 7%, in 2001 and 2002, because of the business cycle and because of 9/11. The number of departures and average delays follow the demand pattern, although there seems to be a lag in the response (departures drop strongly only in 2002). Average fares are around $166 in 1998–2000, and fall to ca. $150 afterwards. However, total aeronautical and passenger-based revenue are of the same order of magnitude on average, so that airport revenues per passenger show an increase after the demand shock.[11] In the econometric model, we have experimented with separate estimations for 1998–2000 and 2001–2002, and with yearly models. Results which are of central interest here are not affected. In the rest of the paper, the time dimension is handled by the inclusion of year dummies.

Figure 1 presents the estimated model. It is a system of equations with six endogenous variables, all expressed in logarithms and defined at the level of an airport in a given year:

(1) the average fare for a departing trip (*ln_airportfare*),
(2) aeronautical revenue per passenger (*ln_aero_dept*),
(3) concession revenue per passenger (*ln_conc_rev*),
(4) the number of passengers departing on a flight segment (*ln_pass*),
(5) the number of departing segments (*ln_departures*),
(6) the average delay of flight segments (*ln_airp_alldel*).

(1) ***ln_airportfare*** = airport fare (***ln_pass***, hhi_pass, hhi_WN, carr_per_dest, hub, acluster, *ln_av_dist*, slotconst, year dummies, T-100 dummy, constant)
(2) ***ln_aero_dept*** = aeronautical rev. per departure (***ln_departures***, acluster, num_dest, hhi_pass, hhi_WN, hub, sh_intl_pass, *ln_av_dist*, slotconst, year dummies, T-100 dummy, constant)
(3) ***ln_conc_rev*** = concession rev. per passenger (***ln_pass***, acluster, hub, hhi_pass, hhi_WN, *ln_inccap*, *ln_av_airtime*, sh_intl_pass, year dummies, T-100 dummy, constant)
(4) ***ln_pass*** = passengers (***ln_airportfare***, *ln_fare_other*, ***ln_airport_delay***, *ln_alldel*acluster*, *ln_inccap*, *ln_pop*, *ln_av_dist*, hub, num_dest, acluster, year dummies, T-100 dummy, constant)
(5) ***ln_departures*** = departures (***ln_aero_dept***, ***ln_pass***, ***ln_airport_delay***, *ln_airportdelay_sq*, *ln_airportdelay*hub*, *ln_av_dist*, hhi_pass, num_dest, year dummies, T-100 dummy, constant)
(6) ***ln_airp_alldel*** = delays (***ln_pass***, *ln_cap*, hhi_pass, acluster, hub, slotconst, year dummies, T-100 dummy, constant)

Fig. 1. Specification (***bold*** indicates endogeneity, *italics* indicates logarithms).

[11] Closer inspection confirms that airport revenues do not follow the pattern of demand over time: total aeronautical revenue keeps increasing, and total passenger spending at the airport only falls slightly in 2002. Airport revenue seems less sensitive than fares to fluctuations in demand for air transportation. A potential explanation is that contracts between airlines and airports fulfill their purported role of reducing risks for airport (in exchange for reduced airport control by the airport management, as well as potentially anti-competitive effects in allocating airport access, cf. [13]).

All of the equations include a constant, year fixed effects, and the dummy variable including potential measurement problems in T-100.

The first three equations capture the effect of market characteristics on the average prices paid by passengers and airlines, as follows. First, the average fare depends on trip demand, itself endogenous, and on the degree of competition between airlines at the airport as well as between airports. The indicators of competition are airline concentration at the airport, and the ratio of the number of carriers and the number of destinations at the airport. The effect of airline concentration is allowed to differ between Southwest-dominated and other airports. Fares also depend on average flight distance. Dummy variables allow for differences between hub and non-hub airports, and between airports that are slot-constrained and those that are not. Second, aeronautical revenues per departing flight depend on the volume of departures, and on indicators of the degree of competition at the airport and between airports similar to those used in the fare equation. The share of domestic passengers is included as well, as earlier research suggests that costs and revenues are higher for international passengers [21]. Third, concession revenues are explained by passenger volumes as a measure of potential demand but also of airport size. The hub dummy is included as hub airports may get less revenue from rental car and parking operations. Airport concentration may affect vertical relations between the airport and airlines; the effect of those vertical relations on concession revenues is not clear a priori. Long distance and international passengers are likely to spend more than domestic ones.

The fourth equation estimates market demand for passenger departures from an airport. Local income and population capture overall demand for the airport as an origin and destination, and the airport's hub status is included because hub airports serve passengers for whom the airport is not the travel origin or destination. The average fare and delay at the airport are expected to negatively affect demand, although the fare is measured for the airport as a trip origin, while passenger volumes include hub traffic. For airports in a cluster, the average fare of other airports in the cluster should positively affect demand if the airports are substitutes, and delays may have stronger effects than outside of cluster. Lastly, an airport serving more destinations is expected to attract more passengers.

Fifth, the number of flight departures can be expected to depend strongly on the number of passengers. For constant passenger volumes, higher aeronautical charges, longer flight distances, longer delays, fewer destinations, and airline concentration may affect the number of departures negatively, by promoting use of larger planes.

Finally, delays are endogenous. The explanatory variables are passenger volumes and capacities (as approximated by the maximum passenger volume for the airport between 1998 and 2002) capture the technical aspect of this relationship. The degree of airport concentration, the dummy indicating if an airport is in a cluster, hub status, and the presence of slot constraints are included as well, as economic models suggest interactions between market structure and equilibrium delays.

Endogeneity, as contained in the model, is accounted for through the use of a 3SLS estimator, where the instruments are given by the reduced form of the structural model of Fig. 1.[12] However, the model as such neglects a range of possible endogeneities. For example, the indicators of market structure are treated as exogenous. Clearly, some of them, e.g. airline concentration, could change even in the short run. Furthermore, many variables are crudely measured (e.g. hub status,

[12] OLS results are similar to 3SLS, except for coefficients on endogenous variables.

dominance of an airport by a carrier, airport capacity), and all of them are aggregated to the airport-year level.

Potentially important explanatory variables, like contractually stipulated vertical relations between airlines and airports, as well as horizontal ties between airports (e.g. the joint ownership of New York airports by the Port Authority),[13] and potential product differentiation across airports in a cluster) are not directly measured. The omission of some of these variables can be partly remedied by including airport fixed effects in the estimation. This solution, while superior in principle, is not entirely satisfactory in the present case, for two reasons. First, the limited number of observations, and the lack of independent time series variation among airports, makes it hard to achieve clear econometric distinctions between the fixed effects and explanatory variables of interest. Second, some explanatory variables are measured as time-invariant dummies, so their effect cannot be estimated at all with the inclusion of fixed effects. Our preferred specification does not include the fixed effects, but it does include dummy variables that indicate hub status and the presence of nearby airports, which are more amenable to economic interpretation than airport fixed effects. In the discussion of the results in the next section, we emphasize the specification excluding fixed effects, but refer to the fixed effects results to check whether results are actually driven by idiosyncrasies at one or a few airports.

3. Results

Table 2 contains estimation results for the model of Fig. 1, for 3SLS without and with airport fixed effects. The overall explanatory power of the model is limited unless fixed effects are included. While the demand equations perform relatively well, there is considerable unexplained variation in the price equations and in the delay equation. Regarding the latter, it is worth noting that, while the economic variables are precisely estimated and the coefficients are not sensitive to the particular specification, most variation is explained by the year fixed effects. This indicates that key variables are missing on the right-hand side, making the model of airport delays incomplete.[14]

The results of the airport fare equation are mostly in line with expectations, and correspond to earlier findings.[15] Average airport fares are lower as passenger volumes increase. The "elasticity" of fares with respect to hub status is 0.18, indicating that hub airports charge higher fares than non-hubs. This is consistent with earlier findings, e.g. [2–4,19], and is explained by the fact that a larger airport presence increases the value of an airline at an airport, allowing higher fares. The sign of the effect of the concentration index is as expected, but it is not significantly different from zero, irrespective of whether airport fixed effects are included. This may be the consequence of the difficulty of distinguishing between the effects of hub status and the effect of

[13] Average aeronautical charges at the New York airports are relatively high, which conceivably is the partly the consequence of joint ownership by the Port Authority. If joint ownership restricts competition, then the New York airports should not be seen as a cluster, as the cluster in our model signifies potential airport competition. However, we have estimated the model under the assumption that the New York airports are and are not a cluster, and find that the estimation results are substantially the same in both cases.

[14] As will be seen later, the relatively poor performance of the delay equation potentially explains the estimated effect of delays on demand.

[15] Adding income as an explanatory variable confirms that higher incomes are associated, probably through more price discrimination, with higher average fares [6]. Other coefficients in the fare equation are not affected by the inclusion of income, but the explanatory power of other equations declines more than that of the fare equation increases, leading us to opt for the specification excluding income.

Table 2
3SLS estimation results, 55 airports, 1998–2002 (275 observations)

Equation	No airport fixed effects		Airport fixed effects	
	RMSE	R^2	RMSE	R^2
airport fare	0.1408	0.5803	0.0345	0.9748
aeronautical revenue per departure	0.3548	0.5897	0.1275	0.9470
concession revenue per passenger	0.2611	0.5405	0.0863	0.9498
passengers	0.3346	0.8141	0.0814	0.9890
departures	0.1061	0.9807	0.0313	0.9983
delays	0.3578	0.6072	0.2237	0.8464
Airport fare	Coef.	Std. Error	Coef.	Std. Error
ln_pass	**−0.0519**	0.0187	**−0.3612**	0.0261
hhi_pass	0.0747	0.0714	0.0678	0.0707
hhi_WN	**−0.3544**	0.0723	−0.0061	0.0163
carr_per_dest	**−0.3632**	0.1113	0.0065	0.0369
hub	**0.1779**	0.0291		
acluster	**−0.0938**	0.0186		
ln_av_dist	**0.3828**	0.0427	**0.4153**	0.0542
slotconst	**0.2360**	0.0414		
D1999	0.0109	0.0265	**0.0276**	0.0064
D2000	*0.0485*	0.0265	**0.0859**	0.0071
D2001	−0.0271	0.0265	*−0.0119*	0.0071
D2002	−0.0410	0.0269	**−0.0533**	0.0073
T100 dummy	**0.1087**	0.0249		
constant	**3.4128**	0.2596	**7.4857**	0.4709
Aeronautical rev. per departure	Coef.	Std. Error	Coef.	Std. Error
ln_departures	**−0.1948**	0.0738	**−1.0249**	0.1548
acluster	**−0.1114**	0.0521		
num_dest	−0.0016	0.0010	−0.0001	0.0011
hhi_pass	**0.3791**	0.1866	0.1431	0.4107
hhi_WN	*−0.3714*	0.2136	**0.1891**	0.0948
hub	0.0544	0.0835		
sh_intl_pass	**1.0823**	0.4719	0.5899	1.1280
ln_av_dist	**1.0926**	0.1289	**1.0633**	0.2196
slotconst	**1.0765**	0.1168		
D1999	0.0087	0.0674	0.0406	0.0255
D2000	−0.0308	0.0676	*0.0486*	0.0292
D2001	0.0461	0.0681	**0.1053**	0.0302
D2002	0.1153	0.0709	**0.1570**	0.0344
T100 dummy	−0.1026	0.0642		
constant	1.3036	0.8615	**9.8670**	2.1796
Concession rev. per passenger	Coef.	Std. Error	Coef.	Std. Error
ln_pass	**−0.0853**	0.0367	**−0.5442**	0.0948
acluster	**0.1595**	0.0460		
hub	**−0.1971**	0.0570		
hhi_pass	**−0.8146**	0.1282	−0.0072	0.2781
hhi_WN	0.0752	0.1558	0.0099	0.0645
ln_inccap	0.0744	0.1329	−0.4405	0.3204
ln_av_airtime	−0.1295	0.0818	**0.1356**	0.0649
sh_intl_pass	**1.1193**	0.2083	−1.2130	0.8007
D1999	0.0103	0.0500	**0.0524**	0.0219
D2000	0.0244	0.0519	**0.1166**	0.0410
D2001	*0.1028*	0.0527	**0.2039**	0.0461
D2002	0.0663	0.0531	**0.1663**	0.0473
T100 dummy	**0.1018**	0.0469		
constant	**3.8431**	1.3691	**13.1517**	3.4501

(*continued on next page*)

Table 2 (*continued*)

Passengers	Coef.	Std. Error	Coef.	Std. Error
ln_airportfare	**−0.8243**	0.2595	**−2.3884**	0.1982
ln_fare_other	0.0260	0.0337	**−2.1527**	1.0412
ln_airport_delay	**0.3973**	0.0663	**0.0487**	0.0153
*ln_alldel*acluster*	**−0.2433**	0.0702	−0.0047	0.0138
ln_inccap	**0.7845**	0.1933	**0.4409**	0.1988
ln_pop	**0.2145**	0.0337	*0.3982*	0.2040
ln_av_dist	**0.4226**	0.0972	**1.0385**	0.1355
hub	**0.3124**	0.0615		
num_dest	**0.0085**	0.0006	−0.0002	0.0004
D1999	−0.0117	0.0632	**0.0418**	0.0165
D2000	*−0.1182*	0.0687	**0.1328**	0.0265
D2001	*−0.1289*	0.0726	**−0.0929**	0.0368
D2002	−0.1497	0.0958	**−0.1711**	0.0424
T100 dummy	0.0301	0.0658		
constant	**3.9688**	1.7669	**9.6539**	3.7428
Departures	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**
ln_aero_dept	0.0037	0.0248	**−0.0762**	0.0222
ln_pass	**1.0184**	0.0197	**0.7687**	0.0357
ln_airport_delay	*−0.0808*	0.0470	*−0.0250*	0.0149
ln_airport_delay_sq	*−0.0240*	0.0130	−0.0040	0.0043
*ln_airport_delay*hub*	**0.0462**	0.0096	**0.0358**	0.0103
ln_av_dist	**−0.4109**	0.0459	**−0.3221**	0.0601
hhi_pass	*−0.1017*	0.0577	**−0.2136**	0.1031
num dest	0.0003	0.0002	**0.0015**	0.0002
D1999	0.0148	0.0202	**0.0148**	0.0062
D2000	**0.0694**	0.0222	**0.0305**	0.0080
D2001	0.0241	0.0208	**0.0545**	0.0075
D2002	−0.0329	0.0240	**0.0443**	0.0113
T100 dummy	−0.0267	0.0194		
constant	**−1.7992**	0.2932	**1.4165**	0.5642
Delays	**Coef.**	**Std. Error**	**Coef.**	**Std. Error**
ln_pass	**0.7931**	0.2889	**0.9062**	0.2302
ln_cap	**−0.6048**	0.2894		
hhi_pass	**1.0093**	0.1482	**2.5359**	0.6837
acluster	**0.1057**	0.0467		
hub	**−0.3742**	0.0745		
slotconst	**−0.6274**	0.1068		
D1999	0.0259	0.0695	0.0288	0.0441
D2000	**0.2408**	0.0738	**0.2391**	0.0482
D2001	**−0.2663**	0.0690	**−0.2647**	0.0436
D2002	**−0.8002**	0.0681	**−0.7862**	0.0431
T100 dummy	**−0.1706**	0.0638		
constant	−0.6440	0.5920	**−11.1341**	3.3094

Notes. Coefficients for airport fixed effects are not reported. **Bold type** indicates 95% significance, *italics* indicates significance only at 90%.

airline concentration.[16] We do find that the effect of airline concentration on average airport fares

[16] Extending the data set by six airports (the ones excluded in the preferred estimation because of presumed reporting changes by regional carriers during the sample period) produces a significant and positive effect of the concentration index on fares. Re-estimating the preferred model after eliminating the T-100 dummy variable, increases the estimated coefficient of the concentration index and increases the precision with which it is estimated.

is negative and significant, when Southwest Airlines is the biggest airline serving the airport. This indicates that the "Southwest effect" can be identified at the level of the airport, not just on route levels.[17] Earlier findings in this regard include Morrison [20], who shows that the presence of Southwest at a nearby airport also reduces fares. The negative of effect of the carrier–destination ratio could be expected, as competition is likely to be more intense when carriers offer service to similar destinations. Average fares at airports facing potential competition from other airports are significantly and substantially lower than at airports in single-airport regions, indicating that there is competition between airlines at the level of nearby airports. Similarly, Borenstein [5] provides evidence that the presence of nearby airport reduces the impact of airport dominance on fares.

Slot constraints lead to higher fares. Fares increase with distance, and the year dummies capture the decline of fares after 9/11 and the subsequent reduction in demand for air travel. The year fixed effects are measured with more precision when airport fixed effects are included as well. The T-100 dummy is positive and significant. Since this variable equals one when it is likely that regional carriers were not reporting to T-100 and had a substantial market share during the sample period, this indirectly indicates that fares are higher on average at airports with a substantial presence of regional carriers.

The fairly satisfactory performance of the fare equation suggests that the model and the data, despite their high level of aggregation, capture relevant characteristics of the airline industry. Consequently, we interpret the results for the aeronautical and concession revenue equations—which have received far less attention in the literature—under the assumption that the data and specification are adequate.[18] Taking this approach, the principal result from the aeronautical revenue equation is that the effects of market structure on aeronautical charges are similar to their effects on fares. Specifically, the charges are lower at airports facing potential competition from nearby airports. Next, while the hub effect is not distinguishable from zero, the concentration index now has a positive effect (elasticity of 0.38). Higher aeronautical revenues at more concentrated airports could be the consequence of a transfer of economic profits resulting from airlines' market power at the airport, to the airport. However, the opposite effect of concentration is found in the equation explaining concession revenues, so a composition effect may be at work as well.

As was the case for fares, the effect of concentration on average aeronautical charges is different when Southwest Airlines is the biggest airline: it is reduced to zero, with the qualification that the Southwest effect for aeronautical revenues is less precisely measured than that for fares. Aeronautical charges are lower in clusters, as is expected when airports compete for passengers but also for airline traffic. Slot constraints translate into higher aeronautical revenues per flight, which indicates that they facilitate the capture of scarcity rents by airports.

Aeronautical charges, in particular landing fees, often are based on aircraft weight. Hence, the positive effects of average distance and of the share of international passengers potentially run through their effects on average aircraft size. In fact, the overall results of the aeronautical revenue equation are consistent with a weight-based charging system. In this sense, our model provides econometric support to earlier work stating that charges are poorly related to marginal costs, especially of congestion. At the same time, the charges do respond to market structure,

[17] When fixed effects for airports are included, the Southwest effect is not significant; in the aeronautical revenue equation it even switches sign and becomes significant. This is an instance where the fixed effects specification is less informative, as Southwest dominance is hard to distinguish from an airport fixed effect in our short time series.

[18] Although it is possible that the airport charge variables themselves are prone to measurement error, as mentioned in Section 2.

much in the same direction as would be expected in a system where prices are driven by marginal costs and by market power.

The positive effect of the dummies for 2001 and 2002 indicates that per flight revenues increased with the slump in air travel (as with the fare equation, these effects are estimated with more precision when airport fixed effects are included). This finding presumably is connected to the prevalence of long-run contracts between carriers and airports, because of which aeronautical revenues tend to be less volatile and respond to shocks more slowly than airline revenues.

Just as aeronautical revenue per departing flight declines with the number of flights, concession revenues per passenger decline with the number of passengers, indicating in both cases that they are partly independent of travel volumes. Hub airports earn less concession revenue per passenger. A likely explanation is that a low share of passengers at hubs requires rental car and parking services, which represent a substantial share of concession revenues (cf. Section 2).[19] Increased concentration of airlines at the airports strongly reduces per passenger concession revenues. Although the fixed effects specification suggests this effect may be driven by just a few airports, a plausible interpretation is that increased concentration reduces airport independence, which in turn may lead to transfers from the airport to one or more airlines. However, according to the previous equation, aeronautical revenues increase with airline concentration, so it could be the case that concentration affects the composition of airport revenues. In sum, the effect of concentration on total revenues appears to be ambiguous. It seems likely that the model here suffers strongly from the omitted variables problem (and the associated bias). In particular, variables capturing institutional aspects of the vertical relations between airports and dominant airlines are likely to help distinguish contractual relations from concentration as such. The fixed effects model, where this problem is mitigated, shows no strong relation between concentration and aeronautical or concession charges.

Concession revenues per passenger increase with the share of international passengers, possibly because international travelers spend more time in the airport.[20] The finding that concession revenues are higher in clusters of airports may reflect reverse causality, in that the income variable does not entirely capture the position of the demand function (e.g. because visitors' incomes are not included). An alternative interpretation would be that competition between airports mainly plays out in aeronautical services, and airports in clusters shift revenue-raising activities to concessionary activities.

Passenger volumes for segment departures from an airport decline with the average trip-fares at that airport. The direction of the effect is as expected, but given the differing units of the variables, the coefficient is not interpretable as the fare elasticity of demand. No effect can be discerned of fares at nearby airports. The effect of delays on airport demand is positive, which is contrary to intuition, as passengers are expected to dislike travel delays. A possible explanation is that delays are endogenous, but the delay equation fails to capture key explanatory variables or capacity is inadequately measured (as was argued at the beginning of this section, the limited explanatory power of the equation suggests that this is likely to be the case). If endogeneity

[19] The difference between hub and non-hub airports in the composition of passenger volumes, and its relation to the structure of concession revenues, helps distinguish the hub effect from the airline concentration effect.

[20] The effect is not found when airport fixed effects are included, possibly because international passenger shares are high at the same small number of airports throughout the sample period. Torres et al. [22] find that the probability of positive spending at the airport increases with the length of stay at Asturias airport in Spain, but conditional on positive spending, the amount is independent of the length of stay. Note that, to the extent that the length of stay is correlated with trip length, a positive effect of the average airtime would be expected, but is found only in the fixed effects specification.

of delays is poorly controlled, then the positive effect may reflect that delays are high where demand is high. We do find, however, that the positive effect of delays is considerably smaller at airports in clusters, which indicates that demand responds more strongly to delays—in the expected direction—when alternative airports are available.

Passenger demand for flight segments is higher when incomes and population at the airport's location are higher, and it is higher at hub airports, at airports serving more destinations, and it increases with average segment distance. Demand for departures from the airport rises proportionally with passenger volumes.[21] The remaining right-hand side variables capture effects for constant passenger demand, so relate to responses in terms of airplane size and flight frequency. The finding that the own price effect of aeronautical charges on airplane size is zero (without airport fixed effects) or slightly negative (with airport fixed effects) stands to reason: in a setting where airlines often influence airport decisions, there is no well-defined market, with corresponding prices, for airport access. Delays have a positive effect on airplane size (although precision is limited), except at hub airports, where longer delays lead to more departures—so smaller airplanes—for constant demand. Airline concentration is associated with fewer departures, hence larger planes given demand.

Average airport delays increase with passenger volumes and decline with (our approximation to) airport capacity,[22] but indicators of market structure matter as well, as is suggested by theoretical work on airport pricing and capacity provision. We find that delays are longer in clusters, consistent with theory suggesting that rivalry among congestible facilities may reduce service quality, compared to the monopoly or surplus-maximizing situation [10].[23] Slot constraints lead to lower delays, so the policy seems to achieve its intended direct effect. Airport concentration is associated with longer delays, while hub status negatively affects delays. The negative effect of hub status says that delays at hubs are lower than at non-hubs for equal passenger volumes. These results are found in various tested specifications, but the hub and concentration effects are diametrically opposed to the earlier empirical findings of Brueckner [7] and Mayer and Sinai [18]. These earlier findings are in line with theory which explains lower delays when concentration is higher as a consequence of the internalization by oligopolistic carriers of congestion costs imposed on their own flights.[24] A possible problem of our approach is that the level of aggregation makes it hard to distinguish hub effects from concentration effects. However, it may also be the case that increased concentration leads to strategic manipulation of delays or of airport access in general, for non-dominating airlines, cf. [13], producing higher overall delays on average.

4. Concluding remarks

This paper investigates the effects of market structure on prices that airlines charge to passengers and on prices that airports charge to airlines and to passengers. The endogeneity of the

[21] Alternative specifications show less than proportional increases, without strongly affecting other coefficients. We also experimented with including income on the right-hand side, on the grounds that higher income increases demand for service frequency. The sign of the coefficient is as expected, but is very high, maybe because the data are too aggregated to pick up the connection between income and flight frequencies.

[22] Using flight departures instead of passenger volumes does not affect the nature of the results.

[23] It could also be the case that regions with longer delays are more likely to be served by several airports.

[24] However, Daniel [8] finds that Northwest Airlines does not appear to partly internalize congestion cots at Minneapolis-St. Paul airport, where it dominates. Harback and Daniel [14] find a similar lack of internalization by dominant carriers at many large airports. Mazzeo [17] finds that on-time performance is worse on more concentrated routes, suggesting that concentration may reduce service quality.

demand for trips and for flights, as well as of delays, is accounted for. The empirical results suggest that market structure affects airline fares much as would be expected, and as has been found in earlier work. The results of the demand equations and the delay equations are reasonable as well. The most novel element in the analysis concerns airport charges. We find that airport charges are related to market structure, but the relations seem less straightforward than in the case of fares, especially insofar as vertical relations between airports and airlines are concerned. Furthermore, the results on aeronautical charges are consistent with the widespread practice of weight-based charges, as charges increase with factors that tend to increase airplane size.

One interpretation of our findings is that current airport charging practices are different from what an airport would do if it maximized profits, revenue, surplus, or output. However, the results also show that market structure does affect charges, suggesting that airports are not oblivious to the environment they operate in. Should one expect increased commercialization of airports to drastically change the level and the structure of airport's aeronautical and concession charges? Much depends on how such commercialization will affect vertical relations between airports and airlines. If one assumes that airports will exploit their spatial market power, and are constrained in doing so only by market demand and by the presence of nearby airports, then the pricing structures derived in recent literature apply. Since such pricing schemes are very different from what is currently observed, this would imply that the impact of "commercialization" on airport charges is large. However, airports compete for hub status, where location matters less, and many of them face horizontal competition. In our data set, for example, 30 out of 55 airports are hubs, or compete with other airports, or both. Because of this, the airports may be inclined to offer airlines favorable conditions in return for long-term commitments to their market. While it is not at all obvious that these issues justify current airport business practices, they do point to the limitation of models that emphasize the impact of congestion and spatial market power on airport decisions, and they suggest that airports may be acting rationally when they seemingly transfer part of their market power to airlines.

The analysis is novel in that it provides an integrated treatment of fares and airport charges, but it only scratches the surface and it displays obvious shortcomings. A clearer and more precise picture of the determinants of US airport operating revenues requires at least two improvements. First, the flight and passenger services that the airports provide can be disaggregated. In the present analysis, all variables are defined at the level of an airport. However, many volume-related variables could also be defined in terms of airport pairs per airline, and average fares and delays could be disaggregated to airlines destinations. Such disaggregation would allow a more detailed analysis of the determinants of airport charges, even if airport charges themselves cannot easily be measured at a lower level of aggregation. This disaggregated approach approximates travel markets more closely, and is therefore likely to yield more precise and additional insights. Second, better indicators of key issues, like the vertical relations between airports and airlines, can be constructed. The current analysis assumes that those vertical relations are fully captured by the concentration index, but additional institutional information is likely to refine that picture. Capacity measures could be improved as well, for example by referring to runway and gate availability, as well as gate control.

Apart from the mentioned improvements, future research could focus on the apparent difference in time variation of airport revenues versus airport fares. Inspection of the data suggests that fares are more volatile than airport revenues, and this is corroborated by the econometric results. Our interest in this paper has been limited to checking that the main time patters exhibited do not jeopardize the analysis of the connection between market structure and market outcome, but the issue deserves closer consideration.

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Appendix A. Data sources and construction of variables

The data set covers 55 medium and large hub airports in the US from 1998 to 2002. It is obtained by merging aggregated versions of the following basic sources:

- Form 127 of airports' financial reports ('CATS reports'), downloadable from http://cats.airports.faa.gov/reports/reports.cfm (accessed August 24, 2006), for years 1996 to 2004. The reports summarize the revenues, expenditures, proceeds, investment expenditures, and debt payments of more than 400 US airports. Revenues are described in most detail, including distinctions between subcategories of aeronautical operating revenue, non-aeronautical operating revenue, and non-operating revenue. The data are yearly aggregates.
- The T-100 segment data, which supply information on domestic and international flight segments by US and foreign air carriers, by air carrier, by origin and destination airports, and by service class, for enplaned passengers, freight, and mail. The data are at: http://www.transtats.bts.gov/Tables.asp?DB_ID=110&DB_Name=Air%20Carrier%20Statistics%20%28Form%2041%20Traffic%29&DB_Short_Name=Air%20Carriers (accessed August 24, 2006).
- The airline on-time data, containing per-flight delay indicators. These data contain a smaller number of airports than the other data sets, being roughly limited to the medium and large hubs. They are at http://www.transtats.bts.gov/Tables.asp?DB_ID=120&DB_Name=Airline%20On-Time%20Performance%20Data&DB_Short_Name=On-Time (accessed August 24, 2006).
- Airfare data from the airport competition plans (http://ostpxweb.dot.gov/aviation/index.html; accessed August 24, 2006), which contain (among others) average one way fares per carrier per airport, for years 1998–2002. These data are derived from the DOT's origin and destination survey.
- Variables describing characteristics of the metropolitan area in which an airport is located were obtained from http://www.bea.gov/bea/regional/data.htm (accessed August 24, 2006).
- Dollar values were converted to 2000 prices using the CPI for urbanized areas.

These basic sources are combined as follows. First, only large and medium hub airports within the 50 states plus the District of Columbia are retained. This means that at most 73 airports can be observed for 9 years, i.e. there are 657 potential observations.

The Form 127 data are merged with the T-100 and the On-Time data, after aggregation of the latter two data sets by airport. As On-Time data are on a flight basis and T-100 data are at the month-carrier-route level, the aggregation can be done by origin or by destination airport. Here, we only use the origin-based aggregation (early experiments comparing origin- and destination-based aggregations showed little difference between them). Hence, when constructing variables we only consider US departure airports. Indicator variables are constructed to distinguish US and non-US destinations, and to identify unique segment destinations per origin and carrier. The ratio of the total number of carriers at the airports and the total number of unique destinations gives the carrier–destination ratio, which roughly captures the intensity of competition among carriers. Passenger volumes and the number of departures performed are aggregated, and used to calculate

Table A.1
Included airports with cluster and hub status*

Airport code	Name	acluster	hub	Airport code	Name	acluster	hub
ABQ	Albuquerque Intl.	0	0	MDW	Chicago Midway	1	0
ATL	William B. Hartsfield	0	0	MIA	Miami Intl.	1	1
AUS	Austin-Bergstrom Intl.	0	1	MKE	General Mitchell Intl.	0	0
BDL	Bradley Intl.	0	0	MSP	Minneapolis-St. Paul Intl.	0	1
BNA	Nashville Intl.	0	0	MSY	New Orleans Intl.	0	0
BOS	General Edward Lawrence Logan	0	0	OAK	Oakland Intl.	1	0
BUR	Burbank-Glendale-Pasadena	1	0	OMA	Eppley Airfield	0	0
BWI	Baltimore-Washington Intl.	1	0	ONT	Ontario Intl.	1	0
CLE	Cleveland Hopkins Intl.	1	0	PBI	Palm Beach Intl.	1	0
CLT	Charlotte/Douglas Intl.	0	1	PDX	Portland	0	0
CMH	Port Columbus Intl.	0	1	PHL	Philadelphia Intl.	0	1
DAL	Dallas Love Field	0	0	PHX	Phoenix Intl.	0	0
DCA	Ronald Reagan Washington National	0	0	PIT	Pittsburgh Intl.	0	1
DEN	Denver Intl.	1	1	PVD	Providence Intl.	1	0
DFW	Dallas/Fort Worth Intl.	1	0	RDU	Raleigh-Durham Intl.	0	0
DTW	Detroit Metro Wayne	0	0	RNO	Reno/Tahoe Intl.	0	0
EWR	Newark Intl.	1	1	RSW	Southwest Florida Intl.	0	0
FLL	Fort Lauderdale/Hollywood Intl.	0	1	SAN	San Diego Intl.	0	0
IAD	Washington Dulles Intl.	1	1	SAT	San Antonio Intl.	0	0
IAH	George Bush Intercontinental	1	0	SEA	Seattle-Tacoma Intl.	0	0
IND	Indianapolis Intl.	1	1	SFO	San Francisco Intl.	1	1
JAX	Jacksonville Intl.	1	1	SJC	San Jose Intl.	1	0
JFK	John F. Kennedy Intl.	0	0	SMF	Sacramento Metro	0	0
LAS	Mc Carran Intl.	0	0	SNA	John Wayne-Orange County	1	0
LAX	Los Angeles Intl.	1	0	STL	Lambert-St. Louis	0	1
LGA	La Guardia	0	1	TPA	Tampa Intl.	0	0
MCI	Kansas City Intl.	1	1	TUS	Tucson Intl.	0	0
MCO	Orlando Intl.	1	0				

* The following included airports are slot-constrained: DCA, LGA, JFK.

the concentration index.[25] In addition the passenger share of the largest carrier was retained for each airport. Weighted averages of segment distances and segment ramp-to-ramp times were calculated, using the number of departures as weights (using passenger weights leads to similar estimation results). These data were merged with the fare data from the airport competition plans (leading to loss of observations for 1996, 1997, 2003 and 2004). After this step, $5 \times 61 = 305$ observations remain.

As explained in the text, six of the 61 airports were eliminated from the data set, on the grounds that the reporting status in T-100 for some regional carriers seems to have changed in the period 1998–2002, and this leads to large volume changes within the sample period for those six airports. The airports are ANC, CVG, MEM, ORD, SDF and SLC. Including these airports would introduce mismeasurement, also in endogenous variables.[26] Of course, measurement problems may also occur outside the sample period, at airports with a large presence of regional carriers not included in T-100. To mitigate this problem, we identify airports for which the volume changes in T-100 between 2002 and 2005 are larger than the average volume change across the 61 airports plus one standard deviation (this point happens to coincide with a clear break in the ordered series of percentage increases for 2002–2005). Such large changes occur at the following ten airports: FLL, IND, DCA, PHL, CLT, MKE, RSW, MEM, SLC and IAD.

We estimate the model of point twice: once with the inclusion of a dummy variable that identifies the ten airports for which there are large changes, once after eliminating those ten airports. Including the dummy improves the model fit (and the dummy variable is significant in 4 of the 6 equations), while coefficients of other variables are barely distinguishable from these for the model with 55 airports but without the dummy variable. Eliminating the ten airports has only limited effects on estimates, and it improves the explanatory power of some equations while reducing that of others.

Table A.1 shows the airports included in the final analysis, and whether they are considered as hubs and as part of an airport cluster. The basic clusters are as follows: {(SFO, SJC, OAK), (LAX, BUR, ONT, SNA), (FLL, MIA), (DFW, DAL), (IAH, HOU), (IAD, DCA, BWI), (ORD, MDW), (LGA, EWR, JFK), (BOS, MHT, PVD)}; these definitions are similar to those of de Neufville [11]. Note that clusters were defined before elimination of airports on the basis of T-100 problems, in order to ensure that the dummy indicating potential competition with other airports equals one even if the competing airport ultimately is not included.

References

[1] A.A. Altshuler, D.E. Luberoff, Mega-Projects: The Changing Politics of Urban Public Investment, Brookings Institution, Washington, DC, 2003.

[2] S. Berry, Airport presence as product differentiation, American Economic Review 80 (1990) 394–399 (Papers and Proceedings).

[3] S. Berry, M. Carnall, P. Spiller, Airline hubs: Costs, markups and the implications of consumer heterogeneity, in: D. Lee (Ed.), Advances in Airline Economics, vol. 1: Competition Policy and Antitrust, Elsevier, 2006.

[4] S. Borenstein, Hub and high fares: Dominance and market power in the US airline industry, RAND Journal of Economics 20 (1989) 344–365.

[25] In this paper we only use the concentration measure bases on passenger volumes. Alternative measures, based on seats, departures performed have been experimented with, but did not affect results by much (on this level of aggregation). We use carrier codes as provided in T-100, hence the measures are based on operating carrier rather than marketing carrier.

[26] The explanatory power of the model improves after exclusion of the airports, especially for the aeronautical charges equation.

[5] S. Borenstein, US domestic airline pricing, 1995–2004, Working paper CPC05'048, Competition Policy Center, UC Berkeley, 2005.
[6] J.K. Brueckner, N.J. Dyer, P.T. Spiller, Fare determination in airline hub-and-spoke networks, RAND Journal of Economics 23 (1992) 309–333.
[7] J.K. Brueckner, Airport congestion when carriers have market power, American Economic Review 92 (2002) 1357–1375.
[8] J.I. Daniel, Congestion pricing and capacity of large hub airports: A bottleneck model with stochastic queues, Econometrica 63 (1995) 327–370.
[9] J.I. Daniel, Distributional consequences of airport congestion pricing, Journal of Urban Economics 50 (2001) 230–258.
[10] B. De Borger, K. Van Dender, Prices, capacities and service quality in a congestible Bertrand duopoly, Journal of Urban Economics 60 (2006) 264–283.
[11] R. de Neufville, Management of multi-airport systems—A development strategy, Journal of Air Transport Management 2 (1995) 99–110.
[12] R. de Neufville, Airport Privatization Issues for the United States, MIT, 1999, http://ardent.mit.edu/airports/ASP_papers/airport%20privatization%20issues%20for%20US.PDF#search=%22%22de%20neufville%22%201999%22 (accessed August 28, 2006).
[13] FAA/OST, Airport business practices and their impact on airline competition, Task force study, FAA/OST, 1999.
[14] K.T. Harback, J.I. Daniel, (When) Do hub airlines internalize their self-imposed congestion delays? Economics working paper 2005-08, University of Delaware, 2005.
[15] M. Hartmann, Access to airport facilities: Its impact on market competition, in: D. Lee (Ed.), Advances in Airline Economics, vol. 1: Competition Policy and Antitrust, Elsevier, 2006.
[16] M.E. Levine, Landing fees and the airport congestion problem, Journal of Law and Economics 12 (1969) 79–109.
[17] Ch. Mayer, T. Sinai, Network effects, congestion externalities, and air traffic delays: Or why not all delays are created evil, American Economic Review 93 (4) (2003) 1194–1215.
[18] M.J. Mazzeo, Competition and service quality in the US airline industry, Review of Industrial Organization 22 (2003) 275–296.
[19] S.A. Morrison, C. Winston, Enhancing the performance of the deregulated air transportation system, Brookings Papers on Economic Activity, Microeconomics (1989) 61–123.
[20] S.A. Morrison, Actual, adjacent, and potential competition—Estimating the full effect of Southwest Airlines, Journal of Transportation Economics and Policy 35 (2001) 239–256.
[21] T.H. Oum, Ch. Yu, Measuring airports' operating efficiency: A summary of the 2003 ATRS global airport benchmarking report, Transportation Research E 40 (2004) 515–532.
[22] E. Torres, J.S. Domínguez, L. Valdés, R. Aza, Passenger waiting time in an airport and expenditure carried out in the commercial area, Journal of Air Transport Management 11 (2005) 363–367.
[23] US DOT, Impact of Air Carriers Emerging from Bankruptcy on Hub Airports, Airport Systems and US Capital Markets, US Department of Transportation, December 2003, http://ostpxweb.dot.gov/aviation/domav/dotspecterstudy.pdf (accessed on 10/7/05).
[24] US DOT, Aviation Capacity Enhancement Plan, Federal Aviation Administration, December 2003, http://www.faa.gov/ats/asc/publications/03_ACE/03_ACE.pdf (accessed on 10/7/05).
[25] A. Zhang, Y. Zhang, Airport charges and capacity expansion: Effects of concessions and privatization, Journal of Urban Economics 53 (2003) 54–75.
[26] A. Zhang, Y. Zhang, Airport capacity and congestion when carriers have market power, Journal of Urban Economics 60 (2006) 229–247.