Causes and Effects of Air Traffic Delays:
Evidence from Aggregated Data

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Abstract

This study uses aggregated data on concentration, delays, and airfares from the US airports to shed light on two issues. First, we examine the concentration-delays relationship to contribute to the airport-congestion self-internalization debate. Our study is the first investigation of this issue that uses data on sources of delays. Second, we evaluate whether increases in flight delays result in lower airfares when traveling from an airport. Our empirical results are mixed: while total delays are positively correlated with airport-level concentration (contradicting the self-internalization hypothesis), the variance of delays at larger airports does fall as concentration increases. We also find that an increase in airport concentration consistently decreases the share of delays that can be deemed endogenous to the airline. The negative relationship between delays and prices is confirmed, and estimates of this effect are similar to those found in the relevant literature. Of the various sources of delay, weather and late-aircraft delays have the strongest negative impact on prices.

Keywords: airport congestion, delays, internalization

JEL Codes: D40, L10, L93

1. Introduction

This paper uses airport-level data for primary commercial-passenger airports in the United States (US) to address two important questions. First, we examine the relationship between airport-level airline concentration and delays. This allows us to weigh in on the important and hereto unresolved debate on self-internalization of airport congestion. This debate goes back to Brueckner's (2002) suggestion that airlines with a dominant position at an airport will have an incentive to internalize congestion they impose on their own flights. Second, we quantify the relationship between delays and average airfares for trips originating at an airport, paying particular attention to sources of delays. Specifically, some delays (such as weather delays and tardiness caused by the National Airspace System) can be considered external to the carrier; whereas other delays are under the airline's control. Previous work (Bilotkach and Pai, 2012) suggested a stronger association between external delays and airfares, examining a sample of one-stop itineraries from the US airline market. This study provides a broader examination of this issue.

Our analysis combines data on airport concentration and average airport-level airfares with measures of air traffic delays across the US airline industry. We established a 17-year panel (1993-2009), which allows us to examine the issues at hand over a lengthy time period, and to take advantage of the panel data analysis techniques that control for airport-specific heterogeneity. Our estimation results lend limited support to the airport-congestion self-internalization hypothesis. We strongly confirm the robustness of Brueckner's (2002) empirical evidence to other measures of flight delays using 1999 data (as in Brueckner's seminal paper). Yet, cross-sectional analysis for other years is only weakly consistent with the implied negative relationship between airport concentration and delays. Our panel data analysis results are mixed. We do find that an increase in airport concentration consistently decreases the share of delays that are endogenous to the airline. The negative relationship between delays and prices is confirmed. Of the various sources of delay, weather and late aircraft delays have the strongest negative impact on prices.

The issue of self-internalization of airport congestion is both theoretically ambiguous and empirically unresolved. However, available evidence on the balance leans towards supporting the self-internalization hypothesis. At the heart of the debate is Brueckner's (2002) theoretical argument that dominant airlines will have incentives to self-internalize airport congestion. The basic idea of self-internalization is that, unlike a car on a freeway, an airline is considered to be *non-atomistic* since it generally operates several flights at a given airport. Recognizing that scheduling another peak-hour flight will slow down its own flights as well as those of other carriers, an airline will take into account self-imposed congestion in scheduling decisions. Daniel (1995) and Daniel and Harback (2008) provided an alternative theory, based on a stochastic bottleneck model of a Stackelberg leader with a competitive fringe. They suggested that a dominant carrier's incentive to self-internalize congestion is eliminated by the competitive pressure that fringe carriers exert. Since fringe carriers replace the flights cut by the leader with their services, any leader's attempts to internalize this self-imposed congestion will prove futile. The leading carrier will therefore ignore this self-imposed congestion. In an attempt to reach some agreement on this internalization debate, Brueckner and Van Dender (2008) demonstrated how certain competitive settings will bring about self-internalization, while others will not.[1] More recently, Lindsey et al. (2018) explore from the theory standpoint how self-internalization of airport congestion may affect the nature of equilibrium in a dynamic model of congestion with non-atomistic users.

Empirical studies on self-internalization issue are as follows. Mayer and Sinai (2003a) showed that delays decrease with airport concentration, while delays at hub airports are longer than at non-hubs. Rupp (2009) found that airlines do not internalize costs of air traffic congestion, reversing Mayer and Sinai's conclusions. The difference between the two studies is in the use of delay measures relative to the minimum (Mayer and Sinai) and the scheduled (Rupp) travel time.

Further evidence that supports congestion internalization is provided by Ater (2012), using the data on scheduling at hub airports. Santos and Robin (2010) also offered some evidence in favor of self-internalization, examining delays at European airports in 2000-2004. In an effort to explain why carriers overschedule flights at peak times, Molnar (2013) found that, depending on the time-of-day and connections, the congestion benefits of deterring flights by competitors offsets the operational costs of congestion at hub airports.

Fageda and Flores-Fillol (2016) suggest that the extent of congestion self-internalization depends on the dominant carrier's network structure. Specifically, airlines operating fully connected networks will be more inclined to internalize congestion than hub-and-spoke carriers. Bendinelli et al. (2016) evaluate the effect of low cost airline entry in Brazil on delays, finding evidence for self-internalization of airport congestion on that market. Guo et al. (2018) suggest that self-internalization of congestion can be tested

[1] According to the Stackelberg model, the dominant carrier (leader) schedules flights to preempt scheduling decisions by fringe carriers (followers). However, inconsistent with the self-internalization hypothesis, the motivation to deter followers pushes the dominant carrier to also overschedule flights. Note that this explanation only holds if the leader's scheduling decisions meet an *irreversible* commitment condition, which is not a reliable ssumption to make for the airline industry (scheduling decisions are usually made semi-annually).

through reduced-form price regressions. Interestingly, their results contradict the vast literature on the link between airport dominance and airfares.

The following points differentiate our work from the previous empirical studies on the congestion self-internalization debate. First, we use airport-level data over a relatively long time period, while other studies tended to focus on flight-level data over a short time period. Santos and Robin also used airport-level data for European airports over five-year period. However, they did not use an airport-level fixed effects model as we do. Second, we use a wide array of measures of air travel delay, including the information on the sources of delay. Such information allows us to distinguish (to a degree) between delays that are endogenous and exogenous to the carrier. Previous studies tended to focus on more generic measures of arrival and departure delays.

Other studies on determinants of air traffic delays that do not specifically focus on the self-internalization hypothesis are the following. Mazzeo (2003) showed that flight delays are shorter and experience fewer on (at) competitive routes (airports). Lee and Rupp (2007) examined the relationship between the effort level of pilots and airport delays, finding that pilots' wage reduction affect delays. Prince and Simon (2010) demonstrated that delays increase with the level of multimarket contact between carriers. Ater and Orlov (2015) demonstrated a positive relationship between air traffic delays and the spread of the internet, attributing their finding to the way the internet has changed competition between the airlines.

Studies on the effects of delays are scarce. Focusing on New York's LaGuardia airport, Forbes (2008a) found that the impact of delays on airfares is stronger on competitive routes. Her study suggested that average airfares drop by $1.42 in response to an extra minute of delay. Bilotkach and Pai (2012) used a sample of one-stop itineraries to quantify the relationship between delays at connecting hub airports and airfares. They found that one additional minute of weather delay decreases average fares by between $4.46 and $6.55, while an extra minute of carrier delay results in a $2.70 to $5.13 price decrease. Interestingly, Bilotkach and Pai's estimate of the price effect of extra minute of total delay is similar to Forbes'.

The rest of the paper is organized in a straightforward manner. Section 2 discusses the data we use. Section 3 outlines our estimation methodology. Section 4 presents and discusses the estimation results. Section 5 concludes the paper.

2. Data

Our dataset is a 17-year (1993-2009) panel of airport-level observations on air traffic delays, weather characteristics, average airfares, and other airport-level control variables, covering the entire United States. The US Federal Aviation Administration (FAA) classifies airports as primary and non-primary, using 10,000 passenger boardings per year as the cut-off. For our analysis, we will focus on primary airports. The primary airports are further subdivided by the FAA into non-hub airports, small hubs, medium hubs, and large hubs based on the percentage of total passenger boardings handled by the airport. Specifically, non-hub airports are primary airports that handle less than 0.05% of total passenger traffic on the US market;[2] small hubs handle 0.05 to 0.25% of all passengers. In order to be classified as a medium hub, the airport needs to handle more than 0.25% (but less than 1%) of all passengers. Finally, airports that handle over 1% of all passenger boardings in the US market are classified as large hubs. Note that some airports may change their classification over the years.

Overall, there are 442 airports in our dataset, which are classified as primary in at least one year. Availability of delays data, and the airport fixed effects methodology[3] reduced the number of airports included into our analysis to 232.

2.1. Delay Data

We obtained delay measures at the flight-number level from the Department of Transportation's (DOT) Bureau of Transportation Statistics (BTS) division. BTS aggregates information on airline operations, flight delays, and airfares in the US airline industry. Amongst several databanks provided by BTS, the *On-Time Performance* tables offer data on departure and arrival delays, cancelled and diverted flights, and other flight-level measures for non-stop US flights, beginning in 1987. Delays are measured as the difference between scheduled and actual departure (arrival) times, in minutes. Beginning in June 2003, flight delay minutes by cause of delay are also provided. The delay causes, which are determined by the carriers' automated- and manual-reporting systems, are broadly classified as carrier, weather, National Air System (NAS), security and late aircraft.[4]

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[2] To put this into perspective, 0.05% of total US domestic passenger traffic corresponds to about 300,000 passengers per annum.

[3] Any airport, data for which is only available for one year, is excluded from the sample.

[4] Under the DOT's *14 CFR Part 234* regulations, U.S. airlines accounting for at least 1% of domestic scheduled-service passenger revenues are required to report monthly on-time performance statistics for their scheduled-service flights at large hubs (account for 1% or more of annual domestic passenger enplanements). However, all of the reporting carriers (14) voluntarily file records for *all* U.S. airports they serve on scheduled domestic operations.

Using the On-Time Performance data, we have calculated the following delay measures, by origin airport, for each year:

Departure delay: annual count, average, sum, and variance of departure delays of all flights at a given airport. The average (mean), sum, and variance of delays are measured in minutes delayed. All measures include early (negative) and on-time departures (zero minutes of delays). Departure delay is defined as the difference between actual and scheduled time at which an aircraft leaves the gate.

Route delay: annual count, average, sum, and variance of delay *en route* (from the time an aircraft leaves the departure gate up to the moment it reaches the arrival gate). This delay is defined as the difference between the actual and scheduled elapsed flight travel time.

Total delay: annual count, average, sum, and variance of arrival delay for flights originating at a given airport.

To put these measures into perspective, consider the following example. Suppose a flight scheduled to depart at 9:00 AM leaves the gate at 9:30 AM. Assume further that the scheduled flight time for this service is 2 hours, and it reaches its final destination 1 hour and 50 minutes after leaving the departure gate, still twenty minutes behind schedule. For this flight, we register a departure delay of 30 minutes, a route delay of -10 minutes, and a total delay of 20 minutes. The same flight leaving 5 minutes ahead of schedule and arriving 15 minutes behind schedule will register -5 minutes departure delay, 20 minutes of route delay, and 15 minutes total delay.

FAA considers a flight to be delayed, if the difference between actual and scheduled departure (arrival) time exceeds 15 minutes. According to this definition of delay, and consistent with previous literature (Brueckner 2002; Forbes, 2008a), we calculated the measures for departure, route, and total delays for flights that register over 15 minutes of delay according to each of the three measures we employ.

Then, the count of delay is simply the number of departing flights registering departure, total, and route delay in a year, according to FAA threshold. In the above example, our flight departing 30 minutes and arriving 20 minutes behind schedule would add to count of departure and total delays, but not route delays. The mean delay is computed only for flights that are delayed by at least 15 minutes. The sum of minute delayed is also computed for the flights that are considered delayed according to the FAA

The reporting carriers use automated systems (ACARS, DGS, and/or AFIS) or a combination of automated and manual systems to collect flight-operations data.

threshold. Once again, the flight in our example would add 30 minutes to departure delay, 20 minutes to total delay, and zero minutes to route delay (as the flight itself lasted ten minutes less than scheduled).

From 2003, the database on air traffic delays started attributing delays into one of the five categories: carrier, weather, National Air System, security, and late aircraft. The airlines themselves decide on how to classify the delays according to these categories. In this study, we take the airlines' reporting at face value. Specifically, for the data starting in 2003, we calculated the following measures for all flights originating at a given airport:

Sum of delay (in minutes) by cause: annual total of carrier, weather, National Air System (NAS), security, and late aircraft delays for all flights at a given airport;

Share of delays by cause: annual shares of carrier, weather, National Air System (NAS), security and late aircraft delays (from total delays) for all flights at a given airport.

These calculations are performed for flights arriving at their destination behind schedule. Thus, if a flight was – for whatever reason – delayed at the departure gate, but made up the time *en route* to arrive at its destination on schedule, this flight was not included into our calculations for delays by cause.

Basic descriptive statistics for all our delay measures are reported in Tables 1 and 2. The means and standard deviations are reported separately for all primary airports, as well as for the sub-samples of large hubs, and large and medium hub airports. The obvious reason for focusing on these sub-samples is that they include most, if not all, of the airports prone to congestions and air traffic delays. Frequently, delays at smaller airports are related to congestion at large/medium hubs. Table 1 reports the numbers for all the above-listed measures of arrival, route, and total delays. Descriptive statistics for delays by source are reported in Table 2.

Looking at Table 1, we can note the following facts. First, the number (count) of flights experiencing departure delay is somewhat smaller than the number of flights experiencing total delay, suggesting that, on average, a flight leaving the departure gate on time may be held up either queuing on tarmac, in flight, or taxiing after landing. Further, an average delayed flight leaves the gate at a large hub airport 5 minutes earlier, and reaches it final destination 3.5 minutes earlier, as compared to the corresponding averages for the whole sample. Comparing variances of delays, we can see that departure and total delays are less dispersed at larger airports, while route delays exhibit higher variance at medium and large hubs, potentially reflecting more uncertain queuing times at those gateways.

Looking at the source of delays data, the descriptive statistics in Table 2 show carrier, late-aircraft, and NAS delays as the three nearly-equal and most important sources of delay. Together, the three delay sources are responsible for over 90 percent of all delays. Not surprisingly, late aircraft and carrier delays are responsible for a larger share of delayed flights at large and medium hub airports.

Looking at the source of delays, we can consider both carrier and late aircraft delays to be *carrier-controlled* delays, while other delays are largely *exogenous* to the carrier. We of course understand that this delineation is far from perfect. A late aircraft could be delayed by weather conditions or NAS issues on a previous flight. Similarly, bad weather could prevent the assigned crew from showing up at the hub on time for their next scheduled flight – an event that would be recorded as carrier delay in the data. However, we can see that nearly two thirds of delays are attributed to carrier operations or late aircraft arrival. Even with the above caveat, we can suggest that the carrier's operations make a non-trivial contribution to on-time performance.

2.2. Weather Data

We use the National Oceanic and Atmospheric Administration's (NOAA) Global Historical Climatology Network (GHCN) to calculate annual airport weather variables, from 1993 to 2009. Linking the GHCN's daily weather station data to corresponding U.S. airports, we calculated the following weather variables (Table 3 reports the corresponding descriptive statistics).

Average precipitation: Annual average levels of rain and melted snow (in tenths of mm) at GHCN stations located at/near airports in our dataset.

Average snowfall: Annual average snow depth (in mm) at GHCN stations located at/near airports in our dataset.

2.3. Prices and airport characteristics

Data for the analysis of price effects of delays also come from BTS. The average airport-level prices that we use are computed from a 10% sample of actual itineraries (DB1B).[5] We adjust the BTS reported airfares for inflation with a Consumer Price Index (CPI) deflator, using 1993 as the base year.

Airport-level variables are computed from the BTS *T-100 Segment* tables. These tables include monthly data on all commercial airline services departing from US airports, provided at the airline-origin-

[5] The Airline Origin and Destination Survey (known as the DB1B) is a 10% sample of passenger-airline tickets, which includes itinerary information on origin, destination and other flight details.

destination-aircraft type level.[6] Data on the number of departures performed, available seats, passengers enplaned, and the weight of transported freight and mail are also included in the T-100 tables. After aggregating the data to the year level, and merging regional carriers with their corresponding major airlines,[7] we compute the following airport-level measures using the T-100 data:

Market shares of individual airlines: The share of flights performed by a carrier at a given airport, out of all the flights performed at that airport. Market shares have been computed for thirteen individual major carriers, some of which have not existed for the entire duration of our panel. The main purpose of this variable is to account for possible price changes due to growth of low cost carriers (most importantly, Southwest Airlines and JetBlue Airways).

Airport Level Herfindhal-Hirschmann Index (HHI): The sum of squared market shares, across all of the airlines at an airport. We computed this index based on the flight shares of the airlines in our dataset. This variable will play a key role in analysis of the self-internalization hypothesis.

Total passenger volume: The total number of passengers enplaned at the airport. This variable is a control for scale effects.

Mean distance: The passenger-weighted mean distance of a non-stop flight from the airport.

The descriptive statistics for these variables are reported in Table 4. From that table we can see that larger airports feature both lower levels of concentration and lower average airfares as compared to an average primary airport. Bilotkach and Lakew (2014) provide further breakdown of the airport-level concentration measures across different types of primary airports, and clearly demonstrate that smaller airports exhibit higher concentration levels. Their study also demonstrates a clear relationship between airport concentration and average airfares, in line with what we see in Table 4. Lastly, we see that non-stop flights out of larger airports are, on average, longer-haul (note that we only include the data for US domestic flights into our analysis), and large hubs handle about six times the traffic volume of an average primary airport, confirming the well-known fact that traffic is very unequally distributed across the gateways.

[6] For example, in a given month, American Airlines' Boeing 767-200 services from Los Angeles International (LAX) to O'Hare International (ORD) are separately recorded from services on the same route performed by the carrier using a slightly different Boeing 767-300 aircraft.

[7] Some services, in particular on thinner routes, are delegated by the major carriers to regional airlines, typically using smaller jet and/or turboprop aircraft. The original T-100 table codes regional airlines differently from the majors. Details on the procedure used to merge regionals with the majors are available from the authors upon request.

3. Estimation methodology

Our empirical investigation will consist of two parts. First, we offer an analysis of the determinants of delays, focusing on the congestion self-internalization hypothesis. Second, we examine the effects of delays on prices, extending the literature represented by Forbes (2008a) and Bilotkach and Pai (2013).

Most of our work takes advantage of the panel nature of the dataset – we use an airport fixed effects estimation technique to account for airport-level heterogeneity. However, to motivate our analysis more clearly and provide a bridge to the existing literature, we also conduct a cross-sectional data analysis similar to that executed in Brueckner (2002). The cross-sectional analysis compares delay measures across airports for a given year. The panel data analysis evaluates how delays change over time as airport-level concentration changes, accounting for time-specific airport-invariant, airport-specific time-invariant effects, as well as changes in various airport-level control variables.

The congestion self-internalization hypothesis, if true, will imply a negative relationship between airport concentration and delays. Looking at delays by source, we can separate those into two groups, depending on whether they are endogenous or exogenous to the airline. Specifically, carrier and late aircraft delays are, to a degree, endogenous to the carrier. Carrier delays are typically caused by staffing, fleet planning, maintenance and other issues. While these problems could be outside of an airline's control to some extent, they are not as exogenous to the carrier as weather, NAS, or security delays. Late aircraft delays are 'semi-endogenous', depending on their underlying cause. In our analysis we will therefore pay specific attention to this distinction by running specifications that group Carrier and Late Aircraft delays, as well as Weather, NAS and Security delays, together.

The cross-sectional analysis of the determinants of delays follows Brueckner (2002) by selecting the same 25 delay-prone airports and the same explanatory variables included in the exploratory regressions of the study. Our analysis differs from Brueckner's in two ways. First, we estimate our specification for all the aggregated delay measures at our disposal. Second, in addition to estimating the specification for 1999 (the year reported in Brueckner, 2002), we provide this analysis for 1994, 2004, and 2009 – five years before 1999, as well as five and ten years after that year. In each case, we will estimate the following specification:

$$Delay_i = \alpha_0 + \alpha_1 HHI_i + \alpha_2 Movements_i + \alpha_3 Hub_i + \alpha_4 Slot_i + \alpha_5 Precipitation_i + \varepsilon_i, \qquad (1)$$

where HHI_i is the airport-level Herfindhal-Hirschman index, based on the number of departures; $Movements_i$ denotes the number of aircraft movements (departures) at the airport; Hub_i is the indicator variable for the status of the airport as a hub for a major carrier; $Slot_i$ is the indicator variable for the slot-controlled airport;[8] and $Precipitation_i$ is the annual precipitation at the airport.

The panel data analysis of determinants of air traffic delays consists of estimating simple airport-level fixed effects regressions of the general form:

$$\log(Delay_{it}) = \beta_i + \gamma \log(HHI_{it}) + \delta I_t + \theta X_{it} + \varepsilon_{it}. \quad (2)$$

Here, $Delay_{it}$ is our measure of air traffic delays at airport *i* in year *t*; β_i represent the corresponding airport fixed effects; I_t is the vector of year dummies, with δ denoting the vector of the respective coefficients. The vector of control variables X_{it} includes the following: the natural logarithm of aircraft movements and mean distance of non-stop flight from an airport, as well as the two weather variables and airline market shares. Regressions for the aggregated measures of air traffic delays use the entire length of the panel, whereas specifications using delays by source only use the data for 2003-2009. Note also that the particular functional specification we are using allows us to interpret the key coefficient γ as the respective elasticity.

Further, as we mentioned above, the analysis will be performed both for the entire population of primary airports, and for two sub-samples from this population. Specifically, we will separately consider a subset of large hub airports, as well as another sub-sample, which includes large and medium hubs (as defined by the FAA). We focus separately on these subsets of larger airports, as they are more prone to congestion and delays.

The analysis of price effects of delays will be performed using the airport-level fixed effects specification of the form:

$$\log(Price_{it}) = \beta_i + \mu \log(Delay_{it}) + \delta I_t + \rho W_{it} + \varepsilon_{it}. \quad (3)$$

As before, β_i denote airport-level fixed effects; I_t are year dummies; and W_{it} represents the vector of control variables, consisting this time of the logarithm of airport-level HHI, total number of aircraft movements, mean distance of a non-stop flight, and passenger-based airport-level shares of individual airlines. As noted by Bilotkach and Pai (2013), air traffic delays in price regressions of this type might suffer from the endogeneity problem. Hence, we employ the classical instrumental variable approach to tackle this issue, using our weather variables as instruments for delay measures. Further, we use lagged airport-level HHI and number of aircraft movements as instruments for the corresponding potentially endogenous

[8] These are New York JFK, New York LaGuardia, Washington Regan National, and Chicago O'Hare airports.

variables (following Bilotkach and Lakew, 2014). For the sake of consistency, we will estimate this specification both for the entire population of primary airports, and for the two subsets of larger airports from this population, as identified above.

4. Results

4.1. General

The following tables present our estimation results. Results of the cross-sectional analysis replicating Brueckner's (2002) study for 1999 and 3 additional years (1994, 2004, and 2009) are presented in Table 5. The fixed effects results on the impact of airport concentration on delays and delays by source are provided in Tables 6 and 7, respectively. Results for the second part of our study, examining the price-effects of delays and delays by source, are reported in Tables 8 and 9, respectively.

Altogether, we are working with 12 aggregate measures of flight delays (9 for cross-sectional regressions, where we do not include estimates for the effect of airport concentration on the variance of delays), and 14 measures of delays by source. This amounts to 36 cross-sectional specifications and (given that the analysis is executed for both the entire population of primary airports and the two subsets as identified earlier) 78 specifications for both concentration-delays and delays-price relationships. Presenting full results for 192 specifications is not practical, so our tables only include the key coefficient estimates. Thus, Table 5 contains estimates of α_1 from various versions of specification (1), along with standard errors that are robust to both autocorrelation within and heteroscedasticity across the cross-sections (clustered). Tables 6 and 7 include various airport-level fixed effects estimates of γ from specification (2), with clustered standard errors. Tables 8 and 9 report airport-level fixed effects two-stage least squares estimates of μ from specification (3), also with clustered standard errors.

4.2. Effects of Airport Concentration on Delays: Cross-sectional results for selected years (1994, 1999, 2004, and 2009)

Table 5 reports the results of a cross-sectional analysis that shows the impact of airport-level concentration (HHI) on various measures of delay. The full specification of the regressions replicates regression (1) in Table 2 of Brueckner's (2002) study. Brueckner used 1999 data for 25 congestion-prone US airports. His measure of delay is the total number of delayed flights (or count of delays). We have included 3 more years (1994, 2004, and 2009) of the same analysis in the table for comparison purposes. We can see that the cross-sectional results for 1999 are very well in accordance with the self-internalization hypothesis. HHI coefficient is negative in most specifications and nearly consistently significant across various measures of delay. We use boldface font to denote the specification that is most closely equivalent to Brueckner's (2002) regression we are replicating. The corresponding coefficient from that paper (-17,093) differs from the one we find (-28,046) for that year in a specification that uses an equivalent measure of delay (count of delays over 15 minutes). We attribute this discrepancy to potential measurement issues in the control variables (e.g., how regional or foreign carriers have been incorporated into HHI measurement, or whether international aircraft movements are included into the total count),[9] coupled with the small sample size.

However, the negative airport HHI-delays relationship does not hold for other years shown in Table 5. In fact, results for 2004 and 2009 suggest that concentrated airports are associated with higher count of delayed flights. Results for 2009 also exhibit a positive relationship between airport concentration and the sum of total delays. We do see sporadic coefficient estimates in cross-sectional regressions for years other than 1999, which are consistent with the self-internalization hypothesis. In particular, airport-level concentration has a negative effect on mean departure delays in 1994, as well as on mean departure and total delays over 15 minutes in 2004. Overall, however, the picture does not appear consistent with the hypothesized negative HHI-delays relationships, once we move away from the 1999 data. Rather than overturning Brueckner's results, to the contrary, we show that his results are robust to various measures of flight delay for the 1999 data. However, our cross-sectional results also demonstrate the need to account for time-specific and airport-specific heterogeneity, taking advantage of the panel nature of the dataset.

We should further stress that, looking at our data, we see substantial variability in most of the delay measures we employ across the years. As an example, consider the count of flights delayed by at least 15 minutes. The un-weighted average coefficient of variation across all the primary airports for which this measure can be computed is 0.49. This means that over the years the standard deviation of the count of delayed flights at an average airport is equal to about half of the corresponding mean, implying a rather dispersed distribution.

4.3. Effects of Airport Concentration on Delays: Airport Fixed Effects

The results for the airport fixed effects analysis of the airport-concentration-delays relationship are presented in Tables 6 and 7. We can immediately note from those tables that few regressions for the entire population of primary airports yield statistically significant coefficient estimates. Further, results

[9] Our measures are based on US domestic market traffic.

for the subsets of large and medium hub airports demonstrate a *positive* relationship between airport concentration and delays for most specifications using count of delayed flights, as well as for two specifications for sum of delays. That is, contrary to the congestion self-internalization hypothesis, increased airport concentration leads to more, not fewer flights being delayed. At the same time, there is some evidence suggesting that increased airport concentration decreases the *severity* of air traffic delays in larger airports. Specifically, higher airport HHI is found to decrease mean delays (even though the corresponding coefficients fail to reach statistical significance at conventional levels). Also, our results quite robustly demonstrate that increased airport concentration is associated with lower variance of delays at larger airports, with the magnitude of this effect varying slightly across specifications. A 10-percent increase in airport-level HHI here decreases variance of delays by 0.9 to 1.5 percent, looking only at statistically significant coefficient estimates.

Results for the effect of airport concentration on delays by source, reported in Table 7, show the following. First, changes in airport concentration do not have a statistically significant effect on the sum of minutes delayed, with some outcomes being rather counter-intuitive. For example, we have little reason to expect airport-level concentration to affect weather delays. However, the corresponding coefficient on concentration is positive and significant in two specifications. Specifications using the share of delays by source, however, yield one very interesting result, which we can consider to present evidence in favor of the self-internalization hypothesis. Specifically, increased airport concentration clearly decreases the share of carrier delays and the sum of shares of carrier and late aircraft delays. Earlier, we mentioned that these delay sources are most likely to be endogenous to the carrier. The magnitude of the effect, however, is not impressive: a 10-percent increase in airport-level HHI decreases the share of carrier delays by around 0.2-0.45 percent, depending on specification and subset of airports.

Overall, results presented in Tables 6 and 7 are mixed, with most relevant coefficients not statistically significant, and some running directly opposite in the direction predicted by the self-internalization hypothesis. While more flights are delayed with increased airport-level concentration, the delays do become less severe, as evidenced by lower variance of delays at larger airports. Further, the shares of delays that are endogenous to the airline are also affected by increased airport concentration in the direction predicted by the self-internalization hypothesis. Numerically, however, the magnitude of any effect of airport concentration on delays is rather small. Thus, even where we can talk about statistical significance of the concentration-delays relationship, there is little to write home about as far as economic significance of this effect is concerned.

One could correctly note that there could be different ways of conducting robustness checks of our results. We have done a couple of those, and results are available from the authors upon request. Specifically, one can rightly question whether using average weather variables is the best way of incorporating effects of adverse weather conditions on flight delays. So we have conducted our analysis also using standard deviations of precipitation and snowfall instead of averages[10]. This modification did not bring any qualitative changes to our results; and changes in the coefficient magnitudes have also been small to moderate at best. Next, we evaluated whether the events of September 11, 2001 might have had any structural effect on the relationship between airport concentration and delays. Notably, our data are reasonably symmetric around the year 2001. We have done this by adding – in the spirit of difference-in-differences estimation strategy – the log(HHI)*(post-2001) variable to our specifications. Overall, we did not find the evidence for a structural break in the relationship, quite in line with our expectations. Furthermore, when we looked at the aggregate data on air travel delays, as presented by the US Department of Transportation, we noticed at best transitory improvement in airline on-time performance post-9/11. For instance, the share of flight arriving on time went up from 76.6 percent in 2001 to over 81 percent in both 2002 and 2003; however, it went back down to 76-78 percent in the following three years, and stayed in the same territory as pre-9/11 ever since, only crossing the 80 percent mark once (in 2012).

4.4. Price effects of delays

Tables 8 and 9 clearly demonstrate the negative relationship between air traffic delays and average airfares for itineraries originating at an airport, similar to what has been shown in the literature before (Forbes, 2008a; Bilotkach and Pai, 2013). Most relevant coefficient estimates in the tables are negative, and a good number of those reach statistical significance. Of the measures of delay reported in Table 8, the mean and variance of delays exhibit the least robust relationship with airfares. The count of flights delayed by at least 15 minutes exhibits the most robust effect on prices, especially for departure delays. Another interesting result from Table 8 is the negative relationship between prices and variance of delays in some of the specifications.

Table 9 shows that, of various sources of delay, weather and late aircraft delays have the strongest impact on airfares. The relationship is strong in the subset of large hub airports, marginally significant for the entire population, and does not achieve statistical significance at conventional levels in the subset of large and medium hub airports. We should note that weather delays turned out as the more significant

[10] We are grateful to an anonymous referee for suggesting this robustness check.

determinant of prices compared to carrier delays in Bilotkach and Pai (2013). In contrast to that study, carrier delays do not appear as a significant determinant of prices (Bilotkach and Pai did not consider the impact of late aircraft delays in their work). At the same time, Bilotkach and Pai's paper focused on the issue of hub reliability, and their sample included one-stop itineraries going through hub airports. Finally, looking at specifications that add up endogenous (carrier and late aircraft) and exogenous (weather, NAS and security) delays, we see that the former appear to have a stronger impact on prices in the subset of large hub airports, while the latter show up as a stronger determinant of airfares in the entire population of primary airports. Yet, statistical significance of the corresponding coefficient estimates is marginal in both cases.

To compare the magnitude of the price effects of air travel delays with those from the literature, Table 10 converts elasticities reported in Table 8 into dollar figures for the FAA's definition of delays (flights that are delayed by at least 15 minutes). All of the estimates show the impact of delays on average airfares, provided for the sample mean delay measures. We should note that, just like our original price variable, the estimates in Table 10 are in year 1993 dollars. The US Bureau of Transportation Statistics reports that real airfares in the US domestic market have dropped by about 15 percent between 1995 and 2013, while consumer price index increased by over 60 percent over the same time period.

More specifically, Table 10 evaluates price changes due to the following hypothetical events. First, we suppose that the number of flights delayed by over 15 minutes increases by one percent. The price effect of this change is calculated directly from the elasticity values reported in Table 8, and imply a $0.66-1.33 decrease in average airfares. We proceeded by computing the effect of increasing the mean delay by one minute, for flights delayed by 15 minutes or more. Only one of the regression coefficients for this measure is statistically significant at conventional levels, implying that the extra minute of total delay would decrease the average airfare for flights originating at large hub airports by 58 cents in 1993 dollars.

To evaluate the price effects of an increase in the sum of minutes delayed, we have computed the price effect of increasing the delay of every otherwise delayed flight by one minute. That is, we simply added the count of delayed flights to the total minutes delayed. The corresponding estimated price effect is in line with both common sense and the existing literature. Looking at the results for the population of all primary airports, a one-minute increase in delays is associated with a $1.97-2.25 drop in average fares. The price effect of increasing departure delays for every flight, otherwise delayed by at least 15 minutes, and originating at a large hub airport, is $1.39. These estimates are comparable to $1.60 drop in average fares from an extra minute of total delay, reported by both Forbes (2008) and Bilotkach and Pai (2013).

Variance of delays for flights delayed by at least 15 minutes does not have a statistically significant effect on air fares. Still, we report the price effects of increasing such variance by 1 percent, for completeness. Increasing variance of route delays by one percent for the entire population of airports is associated with a $1.72 decline in average fares. The corresponding number for the price effect of increasing the variance of departure and total delays for flights originating at the large hub airports is $1.21 to 3.03.

From Table 9, we see very little differences in estimated price elasticities with respect to the sum of minutes delayed for all flights versus flights delayed by over 15 minutes. Then, a 10-percent increase in weather delays will decrease average prices by 0.9 percent ($2.75) in the population of primary airports, and by 2 percent ($5.37) in the subset of large hubs. The latter estimate is similar to the price effect of an extra minute of weather delay, reported by Bilotkach and Pai (2013) at their sample mean.[11] The corresponding numbers for price effects of the 10-percent increase in the late aircraft delay are $4.60 and $5.10. At the same time, considering that the share of the late aircraft delay is higher than the same number for the weather delays, the marginal price effect of an extra minute of late aircraft delay will be smaller than for the weather delay. Our results thus confirm Bilotkach and Pai's finding that delays exogenous to the carrier tend to have a stronger effect on airfares compared to equivalent delays that are under the airline's control.

4.5. Schedule manipulation

In using the delay measures relative to the scheduled time rather than the minimum possible flight time, we are largely following the approach adopted by Rupp (2009). Mayer and Sinai (2003a) and Ater (2012) advocated using what they call "excess time" as the proper measure of delay. This measure is defined as the difference between the actual and the theoretical minimum flight times between two airports. Ater correctly noted that the measures of delay we are using could be subject to manipulation by the airlines. Yet, Mayer and Sinai (2003b) concluded – based on analysis of schedule data for millions of flights – that airlines appear to follow a very simple scheduling algorithm. The scheduled flight time tends to be set close to the minimum allowed under the Federal regulations. Deshpande and Arikan (2012) provided another examination of the determinants of scheduled flight time. They found that the scheduled block time positively depends on the number of flights scheduled close to the given flight's departure time.

[11] In Bilotkach and Pai's sample, an extra minute of weather delay is equivalent to over a 10-percent increase in the mean of this delay metric.

Let us also evaluate what kind of bias this potential schedule manipulation might introduce. If the self-internalization hypothesis is true, the dominant airlines at the airports should more correctly account for the expected congestion cost when making their scheduling decisions. This will imply longer scheduling time, consistently with Ater's finding that more concentrated banks at hub airports tend to be longer, and in line with Deshpande and Arikan's (2012) results. Thus, if nothing else changes (i.e., all planes land at the same time as before), schedule adjustments consistent with the self-internalization hypothesis should lead to an improved on-time performance (if delays are measured as the difference between the actual and the scheduled time). Thus, by using a delay measure that is linked to the scheduled time, we are likely biasing the results against us: if we find the evidence consistent with the self-internalization hypothesis, this could be due to either self-internalization or schedule manipulation. At the same time, if we find evidence that is not consistent with self-internalization hypothesis, it will be difficult to imagine a scenario where airlines' schedule adjustment could have negated any potential effect of congestion self-internalization, yielding us to conclude that self-internalization is not present when in fact it does.

To further address this issue of schedule manipulation, we have run an airport-level fixed effects regressions similar to specification (2) with average scheduled time as the dependent variable. The results, which are available from the authors upon request, demonstrate that airport concentration does not have any impact on the length of the time block for which flights departing from an airport are scheduled. Most of the within-airport variation in this measure is explained by the mean distance of non-stop flights, year dummies, and some of the airline-specific effects. Interestingly, competition between the airlines on routes originating at an airport increases the scheduled flight time. We attribute this to airlines seeking minimum differentiation in their scheduled departure times, as documented in Borenstein and Netz (1999). For example, suppose an airline schedules its flight to depart at 8:00 AM. When a new entrant appears and schedules a flight on the same route at 7:55 AM, the incumbent may reschedule its flight to 7:55 AM as well (perhaps to appeal to business travelers seeking to depart as early as possible), without changing the scheduled arrival time.

With respect to the analysis of the price effects of delays, looking at the measures of delay relative to the flight schedule is the most appropriate thing to do. As Rupp (2009) noted, "passengers may be apathetic towards excess travel time", while being "keenly aware of arrival and departure delays", which they will evaluate based on when, relative to the scheduled time, the flight operated.

5. Concluding Comments

This paper examines two issues related to one highly visible and important externality – airport congestion. Air traffic delays regularly attract considerable attention from the media, passengers, and the government. For instance, the summer of 2007 saw the worst airline on-time performance on record in the US airline industry, prompting then President George W. Bush to urge action to reduce delays in the future. Following highly publicized long tarmac delays during the 2008-2009 winter travel season, a law passed in 2009 in the US, known as the Passenger Bill of Rights, provides for substantial financial penalties to the airlines for keeping passengers in an aircraft on the tarmac for more than three hours. In November of 2011, for example, American Eagle (a regional carrier owned by American Airlines) was fined $900,000 for fifteen separate violations of this law.

Policy debates on alleviating the airport-congestion problem focus both on technological solutions (e.g., the NEXTGEN air traffic control system currently being implemented by the FAA), and potential use of economic instruments, such as congestion pricing. The latter is however mostly confined to academic debates, as the current Federal institutional framework related to airport infrastructure financing makes implementation of congestion pricing at US airports next to impossible (see Bilotkach, 2018, for a relevant discussion). The key issue in the academic debate on proper economic instruments for dealing with airport congestion is the so-called congestion self-internalization hypothesis, a suggestion that dominant airlines at concentrated airports will have an incentive to self-internalize the congestion externality. This issue is theoretically ambiguous. The empirical evidence on this hypothesis has also been conflicting, while we must admit that the academic literature has accumulated more evidence in favor of the hypothesis rather than against it.

What differentiates our study from previous work on the self-internalization issue is the use of various measures of air travel delays, including the information on sources of delays. We do this at the expense of aggregating the data to the airport-year level and setting up a 17-year panel for the entire population of primary airports in the US. Future work could analyze these measures of delay (especially considering delays by source) with more disaggregated data.

Our study lends little robust support for the congestion self-internalization hypothesis. While we demonstrate that increased concentration at larger airports leads to more flights being delayed, our data analysis also shows that delays become somewhat less severe – variance of delays decrease with airport-level concentration in the panel data setting. We also demonstrate that higher airport concentration decreases the share of delays attributable to the carrier's actions rather than external causes. At the same time, many relevant coefficients are not statistically significantly different from zero, and some run totally contrary to what self-internalization would predict.

Airline on-time performance is also acknowledged to be an important measure of service quality (Mazzeo, 2003). We contribute to the small body of work quantifying price effects of this delay measure. Many of our estimates are in line with those reported in previous studies. We also identify two sources of delays – late aircraft and weather – that have robust impacts on airfares. The former of the two is assumed to be controlled by the carrier, while the latter is not. Even though estimated price elasticities with respect to these delays are similar (at least in the subset of large hub airports), the marginal price effect of an extra minute of weather delay is higher than the same number for late aircraft delays.

Overall, our study demonstrates that the airport-congestion self-internalization hypothesis does have some merit. Increased airport concentration makes delays at larger airports more frequent, but somewhat less severe, and decreases the share of delays attributable to the carriers' operations. Yet, the economic significance of the estimated airport-concentration-delays effect is not impressive, and does not sufficiently support the need for airport-congestion prices that are inversely proportional to a carrier's share of operations at an airport.

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Table 1 Descriptive Statistics for annual Delay Measures

	All primary airports (4,089 and 4,037 obs.)	Large hubs only (541 obs.)	Large and medium hubs (1,214 obs.)
Count of delays			
Departure Delays	4,034 (9,325)	21,461 (16,436)	12,177 (13,911)
Route Delays	1,751 (3,954)	9,528 (6,485)	5,251 (5,853)
Total delays	4,900 (11,074)	26,237 (18,762)	14,763 (16,356)
Mean (minutes of delay)			
Departure Delays	58.24 (12.36)	53.28 (6.77)	53.27 (7.23)
Route Delays	27.76 (3.72)	29.59 (3.16)	28.78 (2.79)
Total delays	53.94 (10.88)	50.47 (6.34)	50.41 (6.52)
Sum (minutes of delay)			
Departure Delays	218,598 (513,614)	1,150,828 (940,068)	651,814 (778,234)
Route Delays	52,695 (125,390)	291,650 (217,418)	158,725 (189,761)
Total delays	253,559 (590,122)	1,347,617 (1,055,674)	756,546 (889,930)
Variance of delays			
Departure Delays	4,088 (5,280)	2,711 (1,555)	2,901 (1,846)
Route Delays	296.59 (301.11)	379.55 (189.01)	338.53 (193.43)
Total delays	3,511 (4,060)	2,449 (1,227)	2622.24 (1,435.21)

Notes: this table includes mean values, with standard deviations in parentheses. Only data for primary airports (those handling over 10,000 passengers per year) are used in calculations. We use FAA airport classifications, as described in the paper. Only flights delayed by at least 15 minutes are included into calculations.

Table 2 Descriptive Statistics for Delay Measures, by Source of Delays

	All primary airports (1,979 obs.)	Large hubs only (226 obs.)	Large and medium hubs (505 obs.)
Sum of delays			
Carrier	72,176 (196,230)	457,696 (401,168)	247,834 (330,135)
Late aircraft	93,650 (250,083)	556,761 (531,465)	323,134 (416,561)
Weather	15,231 (48,843)	93,598 (116,471)	50,110 (87,635)
NAS	79,616 (181,811)	457,872 (330,797)	264,184 (287,286)
Security	484.54 (1,507)	2,883 (3,527)	1,610 (2,664)
Share of minutes of delay by source			
Carrier	0.275 (0.128)	0.292 (0.092)	0.260 (0.081)
Late aircraft	0.338 (0.163)	0.348 (0.097)	0.380 (0.098)
Weather	0.076 (0.073)	0.052 (0.031)	0.047 (0.026)
NAS	0.307 (0.143)	0.306 (0.080)	0.310 (0.091)
Security	0.004 (0.016)	0.002 (0.002)	0.002 (0.0002)

Notes: this table includes mean values, with standard deviations in parentheses. Only data for primary airports (those handling over 10,000 passengers per year) are used in calculations. Only flights delayed by at least 15 minutes are included into calculations.

Table 3 Descriptive Statistics for Weather Measures

	All primary airports	Large hubs only	Large and medium hubs
Average Annual Precipitation (inches)	35.82 (22.14)	35.42 (16.81)	35.65 (17.69)
Average Annual Snow Depth (inches)	35.49 (50.15)	22.70 (25.87)	26.54 (49.00)

Notes: this table includes mean values, with standard deviations in parentheses. Only data for primary airports (those handling over 10,000 passengers per year) are used in calculations.

Table 4 Descriptive Statistics for Airport-Level Traffic Measures

	All primary airports	Large hubs only	Large and medium hubs
Real airfare (1993 dollars)	306.66 (109.86)	268.45 (67.87)	247.86 (67.94)
Airport-level HHI	0.5121 (0.3040)	0.3208 (0.1819)	0.2832 (0.1736)
Total Movements	25,222 (53,841)	160,722 (85,982)	96,915 (82,924)
Mean Distance (miles)	453.23 (398.18)	1,132.68 (495.81)	888.96 (457.58)
Individual Airline Market Shares			
American Airlines	0.0316 (0.0583)	0.0366 (0.0188)	0.0440 (0.0299)
Alaska Airlines	0.0262 (0.1250)	0.0116 (0.0168)	0.0136 (0.0249)
JetBlue Airways	0.0024 (0.0139)	0.0058 (0.0104)	0.0054 (0.0112)
Continental Airlines	0.0241 (0.0514)	0.0358 (0.0186)	0.0387 (0.0242)
Delta Air Lines	0.0355 (0.0665)	0.0367 (0.0187)	0.0422 (0.0259)
Frontier Airlines	0.0084 (0.0320)	0.0170 (0.0180)	0.0139 (0.0189)
Air Tran Airways	0.0074 (0.0257)	0.0114 (0.0148)	0.0108 (0.0169)
America West Airlines	0.0087 (0.0296)	0.0280 (0.0214)	0.0274 (0.0285)
Northwest Airlines	0.0316 (0.0626)	0.0361 (0.0186)	0.0391 (0.0242)
TWA	0.0121 (0.0394)	0.0254 (0.0275)	0.0255 (0.0309)
United Airlines	0.0272 (0.0543)	0.0362 (0.0191)	0.0416 (0.0271)
US Airways	0.0280 (0.0812)	0.0331 (0.0203)	0.0332 (0.0252)
Southwest Airlines	0.0122 (0.0320)	0.0188 (0.0213)	0.0299 (0.0329)

Notes: this table includes mean values, with standard deviations in parentheses. Only data for primary airports (those handling over 10,000 passengers per year) are used in calculations.

Table 5 Effect of Concentration on Delays: Cross-Sectional Results for Individual Years

	1994	1999	2004	2009
Count of delays				
Departure Delays	-1,639 (3,968)	**-25,692** (7,609)**	12,391 (14,629)	**25,921** (6,415)**
Route Delays	-1,581 (3,776)	**-9,235** (4,029)**	12,410 (8,836)	-113.16 (3,435)
Total delays	-746.68 (4,544)	**-28,046** (12,787)**	**25,506** (11,813)**	**22,198** (5,691)**
Mean (minutes of delay)				
Departure Delays	-7.6575 (9.0213)	-2.0098 (5.3923)	**-16.4084** (7.6286)**	-20.7497 (5.3811)
Route Delays	0.5955 (4.0121)	-0.0797 (4.4359)	-0.3186 (5.2432)	-0.8133 (3.9347)
Total delays	-6.2743 (9.0937)	-8.4581 (6.1870)	**-19.6851** (8.2374)**	**-13.3120** (5.0902)**
Sum (minutes of delay)				
Departure Delays	-198,866 (293,894)	**-1,507,021** (398,201)**	139,968 (798,114)	**1,046,437** (375,722)**
Route Delays	-66,702 (144,292)	**-300,986** (137,141)**	306,767 (295,119)	464.46 (109,916)
Total delays	-212,935 (381,715)	**-1,664,393** (485,916)**	540,097 (787,790)	**969,451** (357,677)**

Notes:

1. Each entry represents the coefficient on airport HHI variable from the regression with the respective measure of delay as independent variable.
2. Variables used in all specifications are the same as in Brueckner (2002). Sample includes 25 airports, also as in Brueckner (2002).
3. White robust standard errors are in parentheses.
4. Conventional significance notation is used: * - 10%; ** - 5%.

Table 6 Effect of Airport Concentration on Delays: Airport Fixed Effects Results

	All primary airports	Large hubs only	Large and medium hubs
Count of delays			
Departure Delays	-0.0441 (0.0918)	**0.2772** (0.1155)**	**0.2071** (0.0920)**
Route Delays	-0.0474 (0.0833)	**0.1896* (0.0999)**	0.0605 (0.0730)
Total delays	-0.0560 (0.0896)	**0.2505** (0.1060)**	**0.1631** (0.0829)**
Mean (minutes of delay)			
Departure Delays	-0.0153 (0.0237)	-0.0817 (0.0904)	-0.0984 (0.0774)
Route Delays	-0.0222 (0.0209)	-0.0130 (0.0727)	0.0190 (0.0544)
Total delays	-0.0075 (0.0219)	-0.0693 (0.1022)	-0.0165 (0.0651)
Sum (minutes of delay)			
Departure Delays	-0.0502 (0.0867)	0.1470 (0.1740)	0.1429 (0.0889)
Route Delays	-0.0795 (0.0961)	**0.1911* (0.1011)**	0.0376 (0.0797)
Total delays	-0.0615 (0.0865)	**0.2134* (0.1157)**	0.1140 (0.0859)
Variance, delays over 15 minutes			
Departure Delays	-0.0816 (0.0552)	-0.1004 (0.0695)	**-0.1497** (0.0628)**
Route Delays	-0.0561 (0.0559)	-0.0132 (0.0999)	-0.0109 (0.0653)
Total delays	-0.0464 (0.0484)	-0.0863 (0.0712)	**-0.1157** (0.0578)**

Notes:

1. Each entry represents the coefficient on the log of airport HHI from the regression with a log of a given measure of delays as the dependent variable.
2. Estimation methodology – airport fixed effects. See Section 3 of the paper for description of all control variables used.
3. Standard errors, robust to autocorrelation and heteroscedasticity, are in parentheses.
4. Conventional significance notation is used: * - 10%; ** - 5%.

Table 7 Effect of Airport Concentration on Delays, by Source of Delays

	All primary airports	Large hubs only	Large and medium hubs
Sum (minutes of delay by source)			
Carrier	-0.0928 (0.0919)	-0.0174 (0.1196)	-0.0626 (0.0947)
Late aircraft	0.0742 (0.1309)	-0.0076 (0.1277)	0.0009 (0.1104)
Weather	**0.4534** (0.2110)**	-0.0029 (0.2714)	0.0626 (0.1596)
NAS	0.1168 (0.0983)	**0.2248* (0.1262)**	0.1303 (0.1103)
Security	-0.1004 (0.2731)	-0.7596 (0.6686)	-0.6493 (0.4041)
Carrier + Late aircraft	0.0099 (0.0658)	0.0096 (0.1004)	-0.0195 (0.0934)
Weather + NAS + Security	**-0.1531* (0.0813)**	-0.3257 (0.2605)	-0.0242 (0.1723)
Share by source			
Carrier	**-0.0262** (0.0132)**	**-0.0314* (0.0165)**	**-0.027** (0.0117)**
Late aircraft	0.0009 (0.0111)	-0.0129 (0.0224)	-0.0032 (0.0154)
Weather	**0.0122** (0.0058)**	--0.0039 (0.0149)	0.0030 (0.0089)
NAS	**0.0162* (0.0082)**	0.0408 (0.0257)	0.0249 (0.0176)
Security	-0.0033 (0.0038)	-0.0008 (0.0014)	-0.0009 (0.0007)
Carrier + Late aircraft	**-0.0204** (0.0079)**	**-0.0451* (0.0234)**	**-0.0319*(0.0163)**
Weather + NAS + Security	**0.0389** (0.0147)**	**0.0507* (0.0297)**	0.0382 (0.0235)

Notes:

1. Each entry represents the coefficient on the log of airport HHI from the regression with a logarithm of a given measure of delays as the dependent variable.
2. Estimation methodology – airport fixed effects. See Section 3 of the paper for the list of control variables included into specifications.
3. Standard errors, robust to autocorrelation and heteroscedasticity, are in parentheses.
4. Conventional significance notation is used: * - 10%; ** - 5%.

Table 8 Price Effects of Delays

	All primary airports	Large hubs only	Large and medium hubs
Count of delays			
Departure Delays	**-0.3530* (0.1840)**	**-0.4947* (0.2742)**	**-0.2151* (0.1201)**
Route Delays	**-0.2677** (0.1269)**	-0.0621 (0.1335)	-0.2845 (0.2262)
Total delays	**-0.3098** (0.1480)**	-0.3519 (0.2192)	**-0.2191* (0.1308)**
Mean (minutes of delay)			
Departure Delays	-1.0171 (0.8963)	-0.5387 (0.3511)	-0.1575 (0.2257)
Route Delays	-1.2441 (1.1188)	-0.8576 (0.7955)	-0.4298 (0.3121)
Total delays	-0.2948 (0.5315)	**-0.2948* (0.1678)**	-0.1675 (0.1393)
Sum (minutes of delay)			
Departure Delays	**-0.3721* (0.1994)**	**-0.2777* (0.1676)**	-0.1410 (0.0856)
Route Delays	**-0.2212** (0.1011)**	-0.0755 (0.1140)	-0.1607 (0.1420)
Total delays	**-0.3330** (0.1664)**	-0.2093 (0.1286)	-0.1243 (0.0835)
Variance of delays			
Departure Delays	-1.1176 (1.9665)	-0.4504 (0.3068)	-0.2113 (0.1382)
Route Delays	-0.5599 (0.4496)	-1.1292 (3.1801)	-0.3635 (0.2812)
Total delays	-0.0820 (0.2772)	-0.7464 (0.5070)	-0.2202 (0.1381)

Notes:

1. Each entry represents the coefficient on the log of the corresponding delay measure from the regression with the log of real average airport-level airfare as the dependent variable.
2. Estimation methodology – two-stage least squares with airport fixed effects. Delays are instrumented with weather variables. See Section 3 of the paper for the list of control variables included into specifications.
3. Standard errors, robust to autocorrelation and heteroscedasticity, are in parentheses.
4. Conventional significance notation is used: * - 10%; ** - 5%.

Table 9 Price Effects of Delays, by Source of Delays

	All primary airports	Large hubs only	Large and medium hubs
Sum (minutes of delay)			
Carrier	-0.3577 (0.3752)	-0.2243 (0.1680)	-0.0585 (0.1337)
Late aircraft	**-0.1668* (0.1011)**	**-0.1981** (0.0993)**	-0.014 (0.0917)
Weather	**-0.0908* (0.0488)**	**-0.2046** (0.1005)**	-0.0237 (0.0519)
NAS	**-0.1436* (0.0755)**	-0.2479 (0.2942)	0.0170 (0.2390)
Security	-0.0951 (0.0729)	0.1755 (0.2636)	-0.0895 (0.1734)
Carrier + Late aircraft	-0.2817 (0.1958)	**-0.2675* (0.1506)**	-0.0282 (0.0964)
Weather + NAS + Security	**-0.1531* (0.0813)**	-0.3257 (0.2605)	-0.0242 (0.1723)

Notes:

1. Each entry represents the coefficient on the log of the corresponding delay measure from the regression with the logarithm of real average airport-level airfare as the dependent variable.
2. Estimation methodology – two-stage least squares with airport fixed effects. Delays are instrumented with weather variables. See Section 3 for the description of all control variables used.
3. Standard errors, robust to autocorrelation and heteroscedasticity, are in parentheses.
4. Conventional significance notation is used: * - 10%; ** - 5%.

Table 10 Marginal Price Effects of Delays, in 1993 Dollars

	All primary airports	Large hubs only	Large and medium hubs
Increase number of flights delayed by 15+ min by 1 percent			
Departure delays	**-1.08***	**-1.33***	**-0.66***
Route delays	**-0.82****	-0.17	-0.87
Total Delays	**-0.95****	-0.94	**-0.67***
Increase mean delay by 1 minute, for 15+ min delays			
Departure delays	-1.75	-1.01	-0.30
Route delays	-4.48	-2.90	-1.49
Total Delays	-0.55	**-0.58***	-0.33
Increase every flight delay by 1 minute, for 15+ min delays			
Departure delays	**-2.11***	**-1.39***	-0.71
Route delays	-2.25	0.66	-1.43
Total Delays	**-1.97****	-1.09	-0.65
Increase variance of delays by 1 percent, for 15+ min delayed flights			
Departure delays	-3.43	-1.21	-0.52
Route delays	-1.72	-3.03	-0.90
Total Delays	-0.25	-2.00	-0.55

Notes: The numbers reported here are effects on average airfares, at the respective sample mean, based on estimates reported in Table 7. Boldface numbers are based on coefficients, significant at 10 percent level or lower.