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Can Airfares Tell? An Alternative Empirical Strategy for Airport Congestion Internalization

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Abstract

In this paper, we propose an alternative empirical strategy to test whether airlines internalize airport congestion corresponding to their share of traffic at the airport. In particular, we construct a hypothesis from theoretical derivation that if airlines do internalize airport congestion the airfare prices would be positively correlated with the interactive term of the airline's passenger number at the origin airport and the congestion delay level of this airport. We test this hypothesis with the Airline Origin and Destination Survey (DB1B) database and the Airline On-Time Performance database published by the US Bureau of Transportation Statistics (BTS). We find that the hypothesis is supported by the data, suggesting that airlines' behaviour is in line with the internalization theory. We further implement subsample analysis and find that airline type also plays a role in this matter. In particular, while full service carriers internalize airport congestion, low cost carriers do not.

KEYWORDS: Airport, Airlines, Congestion Internalization, Market Power, Airfare

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1. Introduction

Congestion is the most visible consequence of excessive traffic and/or operational inefficiency at an airport. Even the smallest holdups in the system can have a dramatic knock-on effect, leading to delays or even missed slots. Aside from frustrated passengers, congestion also causes environment problems due to increased emissions.[1] Numerous studies have been dedicated to the potential solutions of airport congestion, such as congestion pricing. Airport congestion pricing has been extensively discussed, taking into account various factors such as airline market power (e.g., Daniel, 1995; Brueckner, 2002; Pels and Verhoef, 2004; Zhang and Zhang, 2006), airport non-aeronautical revenues (e.g., Oum et al., 2004; Czerny, 2006; Yang and Zhang, 2011; Bracaglia et al., 2014), passenger types (Czerny and Zhang, 2011, 2014) as well as the interactions of these factors (D'Alfonso et al., 2013; Wan et al., 2015). However, in reality airport congestion pricing is still very rare, due to many complicated reasons (e.g., Schank, 2005).

One major obstacle to implement congestion pricing at airports is the dispute around whether airlines internalize congestion corresponding to their share of traffic. In particular, different from road users who are atomistic, the users of airport, i.e., the airlines, usually operate more than one flight. In other words, while road users have no incentive to consider the congestion they impose on other drivers, an airline that schedules an extra flight at a congested airport not only negatively impacts other airlines but also imposes congestion costs on its other flights (Daniel, 1995; Brueckner, 2002; 2005; Nombela et al., 2004; Pels and Verhoef, 2004; Zhang and Zhang, 2006; Basso and Zhang, 2007). Therefore, the airline may have an incentive to restrain from operating too many flights, i.e., internalize the congestion externality imposed on all of its own flights. As

[1] It should be noted that delays are not necessarily evidence of a socially inefficient outcome, but in many cases might reflect the optimal use of scarce runway capacity by hub airlines trying to provide consumers with a large variety of potential destinations and relatively short connections time (see, for example, Mayer and Sinai, (2003)). In other words, there is an optimal level of delay for each and every airport, which can at times be larger than zero.

suggested by Nombela et al. (2004), “Flight delays are a consequence of system overload, even though airport systems operate on carefully planned schedules… airport congestion is a result of decisions of airports’ managers and airlines.” This issue is crucial in designing an optimal congestion pricing for airports, because if self-internalization does exist, airport congestion prices apparently need not be as large as the uniform atomistic prices implied by road-pricing theory. In particular, since airlines operating more flights at the airport tend to internalize a larger share of congestion externality imposed by a marginal flight, they should be less penalized and hence charged a lower congestion price. This seems violating the principle of user pays and makes congestion pricing more controversial. As the key fundamental question of airport congestion pricing, whether self-internalization by airlines exists has been empirically studied in the literature but the findings are in conflict.

Brueckner (2002) as well as Mayer and Sinai (2003) offer empirical evidences in support of the internalization hypothesis, showing that flight delays are lower at highly concentrated airports. Rupp (2009) distinguishes carrier congestion costs, measured as excess travel time, and passenger congestion costs, measured as arrival and departure delays. He finds that airlines might internalize carrier congestion costs, but do not internalize passenger congestion costs. Santos and Robin (2010) study the European airline market from 2000 to 2004 and also confirm the findings of congestion internalization. Ater (2012) hypothesizes that the carrier who operates more flights in a schedule bank should have higher incentives to disperse its flights and reduce flight density at individual points of time in the bank, because a flight is more likely to cause congestion delay to other flights scheduled close to it than those scheduled far away from it. Therefore, empirically he finds that highly concentrated banks tend to be longer and longer banks associate with lower delays. Molnar (2013) finds evidences supporting internalization, suggesting that it depends on the strategic incentives of carriers when balancing the benefits from connections and passenger preferred times with the congestion costs. On the other hand, Daniel (1995) shows that the intraday flight patterns at the Minneapolis-St. Paul airport exhibit too much intertemporal peaking to be consistent with internalization by the dominant carrier (Northwest), and that an atomistic model fits the data better. Daniel and Harback (2008) provide more extensive evidence for this conclusion with a larger number of US airports.[2]

Most of the papers supporting the internalization theory adopt an empirical strategy to test the relationship between airport market concentration and delay. If a significantly negative correlation is found, it is concluded that airlines internalize airport congestion. This empirical strategy links the internalization literature with another relevant strand of literature focusing on the competition-quality relationship in the airline industry. In those papers, flight delay is treated as a measure of quality and is shown to have a positive (instead of negative) correlation with market concentration, as less competition leads to a lower level of service quality (e.g., Mazzeo, 2003; Greenfield, 2014; Bubalo and Gaggero, 2015). To conciliate these two strands of literature, Bendinelli et al. (2016) differentiate the market concentrations at the market level and at the airport level. They propose that airport concentration is more relevant to airport congestion self-internalization while market concentration is more relevant to the competition in the quality aspect of delay. Their empirical findings confirm the existence of airport congestion self-internalization in parallel with market-level quality competition.

However, even controlling for the quality-competition effect, a negative correlation between airport market concentration and delay might not necessarily point to the conclusion of congestion internalization. In particular, with high level of market concentration, the dominant carrier may exercise market power by charging higher price or offering fewer flights with or without airport congestion internalization, thus causing a lower level of delay. Even if airlines do not internalize congestion, ceteris paribus, a highly concentrated airport should have lower delay. In other words,

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[2] See Zhang and Czerny (2012) and Gillen et al. (2016) for some good literature reviews of airport congestion internalization.

market power has two effects on airport delay, one internalization effect and one "residual" market-power effect as named by Brueckner (2002). These two effects have been clearly identified in major theoretical models (e.g., Brueckner, 2002; Zhang and Zhang, 2006; Basso and Zhang, 2007; Silva and Verhoef, 2013), but have not yet been differentiated in empirical studies. Brueckner (2002) and Bendinelli et al (2016) included airport-level traffic as control variables. This method may remove the "residual" market effect but it at the same time removes the effect of congestion internalization due to reduced traffic and hence their results may only capture the congestion internalization achieved by rescheduling the flights but not by reducing traffic via increased price.

In this paper, we adopt an alternative empirical strategy to control for not only the quality-competition effect but also the residual market-power effect, so that the congestion internalization effect can be better measured. The basic idea is that following the analytical airport congestion pricing literature (e.g., Brueckner, 2002; Zhang and Zhang, 2006; Basso and Zhang, 2007), one can conjecture that both congestion internalization and residual market power effects can be reflected in airlines' equilibrium airfares and they give two different markups in the airfares. Empirically, if we include both measure of market concentration and an interaction term of the airline's passenger number at the origin airport and the congestion delay at this airport at the same time, these two variables should capture, respectively, the residual market-power effect and the congestion internalization effect. This is because theoretically the markup of congestion internalization is associated with the airline's total traffic volume at the airport as well as marginal delays. Thus, if the airfares positively correlate with the interaction term, this implies the existence of self-internalization of congestion externality.[3]

[3] It should be noted that airport congestion internalization induces higher equilibrium prices, but may not have a visible impact on traffic level especially in slot-controlled airports. Some papers, including Gudmundsson et al. (2014) and Redondi and Gudmundsson (2016), show how reduced growth opportunities are linked to spillover effects of flights to other substitute airports. Gudmundsson et al. (2014) also point out that the composition of flights can also change with

This empirical strategy leads to a similar model specification applied by Forbes (2008) who studies the impact of market competition and product quality (i.e., delay) on airline price without considering airport congestion internalization. Forbes (2008) regresses airline's price on delay, market share and the interaction term of delay and one minus its market share. The interaction term is to capture the moderation effect of market power on price reduction due to lower level of quality (i.e. more delays). That is, her main finding is that airlines tend to set a lower price due to delays but this price reduction effect is weaker when there lacks a high level of competition. Our approach is different from Forbes (2008) in two aspects. First, we differentiate and take into account two different types of delays: market-level delay and airport-level delay. As pointed out by Bendinelli et al. (2016), delays at the airport level and at the market level should have different implications. Airport-level delay is more relevant to airport congestion internalization, while market-level delay is more relevant to the quality of flight. Forbes (2008) only takes into account market-level delays. Second, we use traffic volume instead of shares as the regressors, as traffic volume is more relevant to congestion internalization than market share. Intuitively, if an airline can have similar traffic volume in two different airports but very different shares at these two airports, its congestion internalization in these two cases should be the same.

The rest of the paper is organized as follows. Section 2 lays out theoretical foundation for the empirical model. Section 3 specifies the empirical strategy and describes variables and data sources. Section 4 presents empirical results and discussion. Section 5 contains concluding remarks.

2. Theoretical Foundation

In order to test whether airlines internalize airport congestion, we follow the theoretical literature to show the airfare structures with or without internalization. The purpose is to identify the term that

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airport congestion, as the increased value of slots (higher landing fees, higher slot prices and growth restrictions) causes the airlines to shift more flights to medium and long-haul operations. We do not consider this situation in this paper.

represents congestion internalization. Then we can use real-life data to figure out whether this term representing congestion internalization plays a role in determining airfares, from which we can conclude whether and under what situations congestion internalization occurs in the context of aviation.

We start with building up a model based on the internalization theory, i.e., we assume that internalization exists. Following Zhang and Zhang (2006), the analysis focuses on individual airports without considering network issues such as the congestion spill/knock-on effect identified by Redondi and Gudmundsson (2016) and Jiang et al. (2016). In addition, only peak period is modeled with the assumption that passengers will not switch between peak and off-peak periods, which means that congestion is always present, an approach that follows Pels and Verhoef (2004). The congested airports are served by multiple airlines, and the airlines choose their flight volumes to maximize profit, i.e., they compete in Cournot fashion.[4] We do not differentiate the types of passengers (e.g., D'Alfonso et al., 2013), nor take into account cooperative relationships between airlines such as code-sharing and alliance (e.g., Jiang et al., 2015). The objective function of airline i is given by:

$$max_{q_{im}} \qquad \pi_i = \sum_m (p_{im} - c_{im} - \beta D_A) q_{im} \tag{1}$$

where q_{im} denotes the traffic volume provided by airline i in market m. Here we assume that aircraft size and load factor are both fixed in all markets and hence traffic volume can be simply

[4] According to the theoretical literature of this research stream, the assumptions on the strategic variables (quantity vs. price), game structure and demand elasticity do affect theoretical prediction on the (non-)existence of self-internalization of congestion externality. However, in any of the theoretical model settings, the judgement on an airline's internalization of congestion externality imposed on its own traffic relies on checking whether airline's decision takes into account one term: marginal congestion cost * airport-level traffic of individual airline. We use Cournot competition in the paper to show how congestion internalization can be reflected in airfare due to the fact that it gives a neat and easy-to-understand way to express the idea. However, we have also carried out the analysis with a Bertrand model, which shows that this way of checking internalization also holds. The detailed derivation for the Bertrand model is available upon request.

represented by the number of passengers instead of using both passengers and flights. This assumption has been widely applied in many theoretical papers to simplify the analysis.[5] p_{im} denotes the airfare (that is a function of q_{im}) in market m, c_{im} denotes the per passenger operating cost of airline i in market m, while βD_A denotes the per passenger congestion cost for airline i at airport A (the origin airport of market m), with D_A being the per passenger congestion delay for the airlines (which is a function of the total number of passengers at airport A, q_A) and β being the unit cost of delay. Note that here we assume that flights originating from the same airport suffer from the same level of congestion delay. Apparently, the markets originating from the same airport are linked to each other through airport congestion. We can obtain the first order condition for airline i and market m as:

$$p_{im} = c_{im} + \beta D_A - p_{im}' q_{im} + \beta D_A' q_{iA} \tag{2}$$

where $q_{iA} = \sum_{m \in A} q_{im}$ denotes the total departing traffic of airline i at airport A, while $q_A = \sum_i q_{iA}$, $p_{im}' = \partial p_{im}/q_{im}$, and $D_A' = \partial D_A/q_A$.

Equation (2) is derived based on the assumption that an airline determines its price by not only taking into account market power as indicated by $p_{im}' q_{im}$, operating cost, c_{im}, and congestion delay cost, βD_A, but also internalizing the marginal (per flight) congestion delay costs encountered by its own flights (or passengers) at the origin airport. Thus, the last term on the right-hand side of equation (2), $\beta D_A' q_{iA}$, represents the markup due to self-internalization of congestion externality. In other words, assuming that all the other factors indeed affect airfare in the way as predicted by equation (2), if airline i does not internalize congestion externality, its airfare in market m should be characterized as:

$$p_{im} = c_{im} + \beta D_A - p_{im}' q_{im} \tag{3}$$

[5] To a certain degree, our dataset can verify these assumptions, as the average passenger number per flight shows only small variations overtime at most airports.

Thus, testing the validity of the self-internalization theory is equivalent to testing the existence of markup $\beta D_A{}' q_{iA}$ in the airlines' ticket price. Equations (2) and (3) can be further synthesized into one single equation:

$$p_{im} = c_{im} + \beta D_A - p_{im}{}' q_{im} + k\beta D_A{}' q_{iA} \tag{4}$$

If $k = 1$, equation (4) is the same as equation (2), meaning that airline i internalizes congestion externality. Whilst, if $k = 0$, equation (4) is equal to equation (3), meaning that airline i does not internalize congestion externality at all.

Breaking down the components of equation (4), we can see that p_{im}, q_{im}, q_{iA} and D_A are directly observable. c_{im} is unobservable but specific to a particular airline in a particular market. Therefore, after controlling an airline's passenger number in each market, the delay level of the origin airport, as well as the unobservable characteristics of the airline, the airport and the market, the airline's level of internalization can be reflected by the relationship between the airfare and the interaction of this airline's passenger number at the origin airport, q_{iA}, and the congestion delay level of this airport. [6]

3. Empirical Strategy

3.1 Empirical model

To empirically test whether airlines internalize airport congestion by applying the idea presented in equation (4), we formulate the following econometric model for estimation:

$$\begin{aligned} ln\,fare_{i,m,t} = \alpha_0 + \alpha_1 lndelay_{A,t} + \alpha_2 lnpassenger_{i,A,t} + \alpha_3 lndelay_{A,t} \times\ lnpassenger_{i,A,t} \\ + \alpha_4 HHI_{A,t} + \delta X_{i,m,t} + i + m + t + e_{i,m,t} \end{aligned} \tag{5}$$

[6] To be more precise, the interaction should be between the airline's passenger number at the airport and the marginal (per flight) congestion at this airport. But marginal congestion is hard to calculate and may generate other technical problems. Molnar (2013), for example, uses an engineering model of runway capacity and queuing to construct measures of marginal congestion. We do not adopt this approach due to two reasons. First, the engineering approach requires a higher level of operational details, which are not available in our dataset. Second, this approach limits the scope of Molnar (2013) to the 35 busiest airports in US (three slot-controlled airports and Honolulu are dropped, leaving 31 airports under investigation). However, as a robustness check we will follow Molnar (2013) to use the rate of airport capacity utilization as an alternative measure of airport congestion in Section 4.3.

On the left-hand side of the model, the dependent variable $ln\, fare_{i,m,t}$ is the average ticket price (in logarithm) charged by airline i in market m in quarter t. A market is identified as a directional direct flight segment from a unique original airport to a unique destination airport. It should be noted that the variable $fare_{i,m,t}$ has a skewed distribution. Taking the log form would make the distribution of our dependent variable approximately normal. Also, the transformation could reduce the influence of outlier observations.

[Insert Figure 1 here]

On the right hand side, we are interested in the interaction term between $lndelay_{A,t}$, the congestion delay level at a particular airport A in quarter t, and $lnpassenger_{A,t,i}$, the passengers number (in logarithm) at airport A in quarter t served by airline i. To make the rest of the discussion easier, from now on, we name $lnpassenger_{i,A,t}$ as airport load by airline i at airport A in quarter t. As discussed in Section 2, this interaction term is relevant to airlines' self-internalization of congestion externality. In particular, α_3 should be statistically larger than zero if internalization of congestion externality indeed occurs, while it should be statistically indifferent from zero if there is no self-internalization.

It should be noted that although equation (4) suggests that air ticket price should be positively correlated with airport delay level after controlling for the interactive term between market passenger number and delay, it is only true on the supply side. However, since a reduced form model is implemented in this paper, both supply side and demand side effects would appear in the estimation. On the demand side, the relationship between air ticket price and airport delay should be negative, as delay is a measurement for air travel quality and should be negatively correlated with airfare (less delay, better quality, and higher price). With this mechanism in play, we are not sure ex ante about whether the relationship between airfare and delay is positive or negative. It is similar for the coefficient of passenger number, if our estimation is negative, it should mean that the demand side effect is stronger than the supply side effect, and vice versa.

Since airlines' equilibrium airfares reflect not only congestion internalization but also residual market power effects, we need to control for the residual market power effects so as to single out the relationship between airfare and congestion internalization. In particular, we calculated the Herfindahl-Hirschman Index ($HHI_{A,t}$) using the passenger numbers of each airline at airport A in quarter t. By incorporating the HHI in the model, we expect to rule out the residual market power effect and competition from the true self-internalization effect.

However, model (5) does not differentiate the quality effect pointed out by Forbes (2008). In order to take that into account, we follow Bendinelli et al (2016) and explicitly distinguish airport-level delays and market-level delays. Model (5) is reformulated as follows:

$$\begin{aligned} ln\,fare_{i,m,t} = {} & \alpha_0 + \alpha_1 lndelay_{A,t} + \alpha_2 lnpassenger_{i,A,t} + \alpha_3 lndelay_{A,t} \times \ lnpassenger_{i,A,t} \\ & + \alpha_4 HHI_{A,t} + \beta_1 lndelay_{m,t} + \beta_2 lnpassenger_{i,m,t} \\ & + \beta_3 lndelay_{m,t} \times \ lnpassenger_{i,m,t} + \beta_4 HHI_{m,t} + \delta X_{i,m,t} + i + m + t + e_{i,m,t} \end{aligned} \tag{6}$$

Model (6) also incorporates the market-level Herfindahl-Hirschman Index ($HHI_{m,t}$) using the passenger numbers of each airline at market m in quarter t. Model (6) could be estimated with the Ordinary Least Square (OLS) regression, yet one primary concern is the potential bias due to omitted variables. The failure to account for omitted market characteristics may introduce bias to our estimation. To alleviate the concern, we control for some key market characteristics $X_{i,m,t}$, which may correlate with our variables of interest and also determine airline's ticket price. The control variables include the distance between original and destination airports (in logarithm), and whether at least one of the endpoint airports of a market is a hub of the airline. These market characteristics have been identified in the aviation literature as important determinants of price and may influence the flight delays (e.g., Ionescu, 2015). To control for other unobservable factors such as supply and demand shocks, as well as time-invariant measurement errors, we include the airline fixed effect i, the market fixed effect m as well as the quarter fixed effect t to capture any confounded factors specific to the airline, the market and the quarter.

At slot-controlled airports, airlines' ability to add extra flights is constrained by the availability of time slots but our theoretical model abstracts away this quantity regulation. Therefore, the relationship between airfares and congestion externality at these airports could be tested with our empirical strategy. To get rid of this regulatory distortion, we exclude observations having at least one endpoint airport being slot-controlled. These slot-controlled airports include John F. Kennedy International Airport (JFK), LaGuardia Airport (LGA) and Ronald Reagan Washington National Airport (DCA) during the sampling period.

Besides, another classical concern is the *endogeneity* problem due to the reverse causality between ticket price and the passenger numbers as well as delays. Precisely, airlines may adopt a low-price strategy to attract more passengers, and thus increase not only passenger numbers in individual market but also the airport load. As a result, increased traffic volume would further increase congestion and delays. If this reverse causality is strong, our estimation could be biased. To address this concern, we replace airport load, flight delays and their interaction term at both airport and market level with their one-year lagged values. While flight delays and traffic volumes of last year may influence the price of this year, the relationship seems less possible to be reversed. The ultimate model specification is as follows:

$$\begin{aligned} ln\,fare_{i,m,t} = \alpha_0 &+ \alpha_1 lndelay_{A,t-1} + \alpha_2 lnpassenger_{i,A,t-1} \\ &+ \alpha_3 lndelay_{A,t-1} \times\ lnpassenger_{i,A,t-1} + \alpha_4 HHI_{A,t-1} + \beta_1 lndelay_{m,t-1} \\ &+ \beta_2 lnpassenger_{i,m,t-1} + \beta_3 lndelay_{m,t-1} \times\ lnpassenger_{i,m,t-1} + \beta_4 HHI_{m,t-1} \\ &+ \delta X_{i,m,t} + i + m + t + e_{i,m,t} \end{aligned} \tag{7}$$

By comparing the results of model (6) and model (7), we are able to check the potential impact of *endogeneity* on our estimations and assess if there is a high level of biasness in our estimates. Finally, we can adopt the Instrumental Variable (IV) approach to address the potential *endogeneity* problem and use alternative measurement of congestion to check the robustness of the estimation results, which we will discuss in details in the later section of robustness check.

3.2 Data and variable construction

Different data sources are used to construct the variables. The major sources are three databases published by the US Bureau of Transportation Statistics (BTS): the Airline Origin and Destination Survey (DB1B) database, the Air Carrier Statistics (T-100) database, and the Airline On-Time Performance (AOTP) database. We use quarterly data from year 2015, the most recent data we are able to obtain in the research period. Data from year 2014 is also used to address the potential endogeneity problem as discussed in the last section.

The DB1B database is a 10% random sample of airline tickets sold by major certified carriers in the US.[7] It is divided into three parts, namely DB1B Coupon, Market and Ticket. The frequency is quarterly and it covers every quarter starting from 1993. We use this database to obtain the average transaction prices for flights of each airline in each market. A record in this database represents a ticket. For each record or ticket, the following variables are available: operating carrier, ticketing carrier, reporting carrier, origin and destination airports, miles flown, type of ticket (i.e., round-trip or one-way), total itinerary fare, and number of coupons. The operating carrier is an airline whose aircraft and flight crew are used in air transportation. The ticketing carrier is the airline that issued the air ticket. The reporting carrier is the one that submits the ticket information to the Office of Airline Information. For the construction of our working sample, we use the ticketing carrier to identify the airline and assume that this carrier pays the cost of operating the flight and receives the revenue for providing this service. This is because we focus on ticket price, which is a decision of the ticketing carriers who actually sell the tickets. This treatment can also eliminate the impacts of the code-shares between network airlines and regional airlines such as American Eagle and Air Wisconsin.

[7] The DB1B database has been widely accepted as a representative sample of the US airline tickets in research papers and industry reports (e.g., Gerardi and Shapiro, 2009; Ciliberto and Williams, 2014).

We apply several selection filters on tickets in the DB1B database. We eliminate all those ticket records with some of the following characteristics: (a) connecting flights, (b) return trips (c) foreign carriers, (d) tickets which are segments of international trips or non-contiguous domestic travel with Hawaii, Alaska and Territories, and (e) tickets with a fare credibility question by DOT. These filters together account for a very small percentage of the records in DB1B 2015. We use the average price of all tickets sold by the same carrier in the same quarter to represent the ticket price.

The T-100 database contains domestic and international airline market and segment data. Certificated U.S. air carriers report monthly air carrier traffic information using Form T-100. From this database, we obtain the total number of passengers served by a particular airline on a particular market (segment) and airport load.

The AOTP database gives information about flight delays. It divides flight delays into five categories: delays due to circumstances within the airlines' control (e.g. maintenance or crew problems, aircraft cleaning, baggage loading, fuelling, etc.), delays caused by extreme weather, delays attributable to the national aviation system (NAS), delays due to previous flight's late arrival (same aircraft), and delays due to security concerns. Among these categories, the NAS delay fits our definition of congestion delay the most, since it includes delays caused by airport operations, heavy traffic volume, and air traffic control. In the paper, we use the average NAS delay at the origin airport as a proxy of airport congestion delays. Compared to previous measures of flight delays in the literature, the NAS delay is a simpler and more relevant measure of delay due to airport congestion (Daniel, 1995; Daniel and Harback, 2008; Brueckner, 2002).

An alternative measure of airport congestion is the rate of airport capacity utilization (Rupp, 2009). The U.S. Federal Aviation Administration (FAA) provide detailed airport profiles for large hub/core airports (FAA, 2014)[8]. Using these profile documents, we can calculate the hourly airport capacity

[8] These airports include ATL, BOS, BWI, CLT, DCA, DEN, DFW, DTW, EWR, FLL, HNL, IAD, IAH, JFK, LAS, LAX, LGA, MCO, MDW, MEM, MIA, MSP, ORD, PHL, PHX, PDX, SAN, SEA, SFO, SLC, TPA, LGB, OAK, SNA.

under all weather conditions. Combined with the actual airport flights information from the T-100 database, we are able to calculate the rate of airport capacity utilization.

Moreover, we follow Snider and Williams (2015) to construct two instrumental variables called AIR-21 and AIR-21_m.[9] Precisely, airports covered by the AIR-21 policy are coded 1 and other airports are coded 0. For the market level instrument, if at least one of the endpoint airport is covered by the AIR-21 policy, the market is coded 1, otherwise, it is coded 0. Section 4.3 provides a brief explanation on AIR-21 policy and its validity as an instrumental variable. The precise definition and summary statistics of these variables used for the empirical test can be found in Table 1 and Table 2.

[Insert Table 1 here]

[Insert Table 2 here]

4. Results

4.1 All carriers

Table 3 presents our main results. In column (1), we run a baseline OLS estimation with the variables of interest only, i.e., the flight delays, airport load, the interaction term and the HHI (c.f. model (5)). To rule out other confounding factors, we excluded the slot-controlled airports, controlled for major market characteristics, as well as the airline, market and time fixed effects[10]. It appears that while the coefficients of delay are negative, the coefficient of interaction term is positive and significant. The results indicate that while airport delay may reduce the average air ticket price, airlines do internalize the congestion delay cost by charging a higher price. They are in line with the prediction of airlines' pricing strategy when they internalize congestion externalities

[9] A more detailed discussion of AIR-21, a brief explanation on AIR-21 policy and its validity as an instrumental variable, is available in Section 4.3.

[10] The distance is market-specific and time-invariant, so it is dropped once the market fixed effect is controlled for.

imposed on their own flights. Besides, we note that airline's flights that link to its hub have significantly higher ticket price, this corresponds to the hub premiums as identified in the literature (Borenstein, 1989).

[Insert Table 3 here]

In column (2), we add market delay, market load and their interaction term (c.f. model (6)) to control for quality-competition effects. At airport level, the coefficient of the interaction term of flight delay and airport load remains positive and significant. The result supports the hypothesis that airlines in general do internalize airport congestion externality. However, we do not find any significant correlation between price and market-level delay. Moreover, we note a negative correlation between air ticket price and airport delay, as delay is a component of the total travel cost of passengers. As pointed out in Section 3, when demand side effect dominates supply side effect, a higher cost of airport delay may mean that the airlines will need to charge passengers for less in order to make flying out of this airport attractive enough. Similarly, the significant but opposite effects of passenger load at airport and market level may suggest that the supply side effect dominates at the airport level, whilst the demand side effect dominates at the market level.

Column (3) addresses the concern about the *endogeneity* problem due to the reverse causality. The ticket price of 2015 is now regressed on the flight delay, airport load and their interaction term of 2014 (c.f. model (7)). It is noted that the market-level HHI at the market level now turns from a negative sign to the normal positive sign, which suggests a correction of the *endogeneity* problem. The results imply that, *ceteris paribus*, a 10% increase in the airport delay will reduce the average air ticket price by 3.5%. However, the coefficient of airport-level interaction term remains positive and significant at 1%, which suggests that airlines with more passenger load will systematically raise ticket price by a larger amount to internalize the congestion cost. Taken together, the consistent results of different model specifications provide robust empirical evidence for airlines' internalization of airport congestion externality, as predicted by many theoretical models.

4.2 Low-cost carriers vs. full-service carriers

Airport congestion internalization is not costless to implement. As we can see from the difference between equations (2) and (3), it requires an airline to incorporate more information into its pricing strategy. Therefore, it may be reasonable to conjecture the existence of heterogeneity in airport congestion internalization across different business models in the industry (i.e., full-service airlines vs. low-cost airlines). We expect different airlines to have different congestion internalization strategies and hence more detailed analysis may provide a better understanding on this issue. To investigate this possibility, we further split the full sample into subsamples of low-cost carriers (LCCs) and full-service carriers (FSCs) and repeat the regression analysis. In particular, we identify Allegiant Air, Frontier Airlines, Spirit Airlines, Sun Country Airlines and Virgin America as major low-cost airlines, and distinguish them from other full-service airlines to contrast their results[11].

The results are presented in Table 4. As in previous analysis, we adopt three different model specifications and controlled for all the fixed effects. Columns (1)-(3) show the results for LCCs, and columns (4)-(6) show the results for FSCs.

[Insert Table 4 here]

Interestingly, while we can still confirm that internalization of airport congestion externality exists for FSCs, we also find that LCCs do not seem to follow suit. One possibility behind this heterogeneity is that LCCs may deliberately choose airports with less congestion so that it is less necessary to internalize airport congestion. After all, LCCs are probably among the ones that dislike airport congestion the most, as congestion reduces aircraft utilization and forces the airlines to burn more fuel. For example, Gudmundsson et al. (2014) argue that LCCs do not operate in the capacity-constrained London Heathrow but have a substantial presence in the other London area airports such as Stansted, Gatwick and Luton.

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[11] We also check the robustness of the results by including JetBlue and Southwest Airlines into the subsample of LCCs and the results are similar and available upon request.

This finding is very important and reinforces previous finding of Mayer and Sinai (2003). It suggests that although we have evidences to support the airport congestion internalization theory in general, the real situation can still depend on the type of airline under investigation. In particular, when designing airport charge, an airport with LCCs as its major customers should probably adopt a different approach compared with one that mainly serves full-service carriers. This point is also validated in the following section.

4.3 Robustness checks

We conduct three robustness checks of our estimation results. One is to use IV estimation to address the *endogeneity* problem of congestion delay. As documented in the literature, in 2000, the U.S. Congress enacted the Wendell H. Ford Aviation Investment and Reform Act for the 21st Century (AIR-21). The AIR-21 policy had effectively reduced barriers to entry at covered airports. However, the increased air traffic, especially due to the low-cost carrier penetration, significantly reduced the on-time performance of covered airports (Snider and Williams, 2015). The AIR-21 policy is thus a good predictor of airport congestion delay. Moreover, the AIR-21 policy had entered into force in 2000, and the last covered airport was Las Vegas McCarran International airport (LAS) in 2005. The historical policy is thus impossible to be influenced by today's confounding factors, which dismiss concerns about the violation of *exclusion restriction* of IV. Therefore, we construct AIR-21_a, AIR-21_m and their interaction terms with the passenger load as instruments for the corresponding airport and market delays and the interaction terms. Still, it should note that the use of AIR-21 is not perfect but subjects to some limits. As the list of AIR-21 covered airports is time-invariant during our sampling period, the control of market fixed effect will drop the IV. With this in mind, we re-estimated model (7) without controlling for the market fixed effect and the results are presented in Table 5.

[Insert Table 5 here]

The second robustness check is to use the airport capacity utilization as alternative measure of congestion delay. One potential concern about the use of NAS delay as a measure of airport congestion is that it still contains other delay causes that may not entail airport congestion, e.g., the ATM delays. In this circumstance, one alternative measure depicting the actual congestion level of airport is desirable to check the bias due to unrelated delays. In the literature, Rupp (2009) calculated the rate of airport capacity utilization to measure the airport congestion. We follow his methodology to calculate the quarterly airport capacity utilization for 34 major airports with available information from the FAA's website. The market capacity utilization is obtained by the mean of capacity utilization for original and destination airports. The use of airport and market capacity utilization is more accurate, yet the restriction of data to 34 airports may induce sample selection bias and reduce the representativeness of our sample. To be more prudent, we only use the airport capacity utilization as a robustness check and estimate the same model (7) as in previous analysis, the results are reported in Table 6.

[Insert Table 6 here]

Moreover, we have also conducted robustness check for the possibly different fare structures between hub and non-hub airports. We define hub flights as flights with at least one endpoint airport being the hub of a particular airline. Then, we split the full sample into hub and non-hub flights and contrast the results. As shown in Table 7, both hub and non-hub flights have similar results of internalization of congestion. Although the hub flights seem to have less significant results, it is likely due to the smaller sample size.

[Insert Table 7 here]

As one can note in Tables 5-7, the main results are consistent and the conclusion remain unchanged, i.e., in general, airline internalize the airport congestion cost other than the market congestion cost. Still, this self-internalization behaviour is not homogeneous, whilst the FSCs systematically internalize more, the LCCs seem not to follow suit. These robustness checks thus lend more confidence to theoretical predictions which support airlines' self-internationalization behavior and our empirical validation.

5. Discussion and conclusion

There exists a debate in literature regarding whether airlines internalize airport congestion externality corresponding to their traffic volume. Both theoretical and empirical evidences point to opposite directions. In this paper, we join the discussion with an alternative empirical strategy. In particular, we obtain a hypothesis from theoretical construct that if airlines do internalize airport congestion the airfare prices would be positively correlated with the interactive term of the airline's passenger number at the origin airport and the congestion delay level of that airport. We test this hypothesis with the DB1B database, the T-100 database, and the AOTP database published by BTS. We find that the hypothesis is supported by the data, suggesting that our empirical finding is in line with the internalization theory. Moreover, we also find that whether the internalization happens or not depends on the types of airlines. In particular, FSCs internalize airport congestion externality while LCCs do not.

The contribution of the paper is two-fold. On the one hand, it provides an alternative empirical strategy to test the airport congestion internalization theory. This empirical strategy has the ability to differentiate the residual market-power effect and the congestion internalization effect, which has never been achieved by previous empirical strategies to our best knowledge and marks a methodological contribution to the literature. On the other hand, our results should give more credibility to the theory supporting congestion internalization and the subsequent policies. More efficient congestion pricing schemes might be possible with the help of our findings. In particular, when congestion internalization is prevalent, the design of congestion pricing will need to take into account the airlines' market shares at the airport, which might appear controversial as heavier airport users would be charged with a lower fee per passenger/flight. Other than the result, we believe that this study also offers a very easy way for the airports to test whether congestion internalization appears in any specific case, which can be a more meaningful contribution of this paper.

A few limitations exist in this paper. First and foremost, we mainly use simple measurements to obtain values for the explanatory variables, including per flight delay and marginal per flight delay at the airports. Some remedies such as fixed effect analysis are implemented but we might still be able to achieve better estimations with more accurate measurements, which is a possible research venue for further study. Second, some necessary simplifications have been made for the theoretical derivation, such as the omission of airline network. In reality, however, due to the prevalence of the hub-and-spoke network, connecting flights might affect non-stop flights in one way or another. Our empirical study does not take into account this issue, which will again be an interesting venue of future research. Last but not least, we do not claim that this paper has solved the debate on the issue of airport congestion internalization. Even with the new evidences that we show with this paper, the question still persists. In fact, it is not surprising that our results support the "pro-internalization" theory, as although we have adopted a different empirical strategy from the previous papers, the foundation of our paper is still from the economic theory, which are closer to Brueckner (2002) and Mayer and Sinai (2003) compared with the more engineering perspective of Daniel (1995) and Daniel and Harback (2008). Further studies should ensue to reconcile these two streams of literature.

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Table 1. Variable definitions and sources

Variable	Definition and measure	Unit	Year	Source
Panel A: Variables of main specifications				
lnDelay_a	The average delay attributable to the national aviation system (NAS) at the original airport (in log).	Minutes	2014-2015	AOTP
lnPassenger_a	Number of passengers carried by an airline at the original airport (in log).	N.A.	2014-2015	T100
HHI_a	The Herfindahl-Hirschman Index of the original airport calculated using the passenger numbers.	N.A.	2014-2015	T100
lnDelay_m	The average delay attributable to the national aviation system (NAS) in a particular route (in log).	Minutes	2014-2015	AOTP
lnPassenger_m	Number of passengers carried by an airline in a particular route (in log).	N.A.	2014-2015	T100
HHI_m	The Herfindahl-Hirschman Index of a particular route calculated using the passenger numbers.	N.A.	2014-2015	T100
lnFare	Air ticket price for a direct flight from an original airport to a destination airport (in log).	US dollar	2015	DB1B
Hub	Dummy variable indicating whether at least one endpoint airport is the airline's hub.	N.A.	2015	Own elaboration
lnDistance	Great circle distance between an original and a destination airport of a particular route (in log).	Kilometers	2015	DB1B
LowCost	Dummy variable indicating low cost airlines, i.e., Allegiant Air (G4), Frontier Airlines (F9), Spirit Airlines (NK), Sun Country Airlines (SY), Virgin America (VX).	N.A.	2015	Own elaboration
Panel B: Variables of robustness check				
Utilization_a	The original airport capacity utilization by dividing the number of actual flights by the airport's quarterly capacity.	percent	2014-2015	FAA(2014)
Utilization_m	The average capacity utilization of original and destination airports of a particular route by dividing the number of actual flights by the airport's quarterly capacity.	percent	2014-2015	FAA(2014)
AIR-21_a	Dummy variable indicating whether an original airport is covered by the AIR-21 policy.	N.A.	2000	Snider and Williams (2015)
AIR-21_m	Dummy variable indicating whether an original or a destination airport of a particular route is covered by the AIR-21 policy.	N.A.	2000	Snider and Williams (2015)

Table 2. Summary statistics of main variables

	2014					2015					
Variable	Obs	Mean	Std.Dev.	Min	Max	Obs	Mean	Std.Dev.	Min	Max	P value of t-test
lnDelay_a	33709	2.669	0.320	0	4.190	36789	2.672	0.288	0	4.382	0.000
Utilization_a	22303	0.278	0.117	0.021	0.662	22303	0.228	0.069	0.019	0.367	0.000
lnPassenger_a	36837	11.90	1.918	0	16.03	37588	12.03	1.851	3.219	16.07	0.000
HHI_a	37588	0.330	0.208	0	1	37588	0.321	0.200	0.084	1	0.000
lnDelay_m	26485	2.400	0.676	0	5.638	32394	2.383	0.694	0	4.875	0.001
Utilization_m	10346	0.271	0.101	0.062	0.639	10346	0.222	0.050	0.057	0.359	0.000
lnPassenger_m	23958	4.043	1.679	0.693	8.371	37588	3.875	1.802	0.693	8.178	0.000
HHI_m	37588	0.575	0.369	0	1	37588	0.634	0.273	0.141	1	0.000
lnFare	N.A.	N.A.	N.A.	N.A.	N.A.	37588	5.521	0.674	0	9.224	N.A.
Hub	N.A.	N.A.	N.A.	N.A.	N.A.	37588	0.207	0.405	0	1	N.A.
lnDistance	N.A.	N.A.	N.A.	N.A.	N.A.	37588	6.587	0.708	4.220	8.510	N.A.
LowCost	N.A.	N.A.	N.A.	N.A.	N.A.	37588	0.119	0.324	0	1	N.A.
AIR-21_a	N.A.	N.A.	N.A.	N.A.	N.A.	37588	0.579	0.494	0	1	N.A.
AIR-21_m	N.A.	N.A.	N.A.	N.A.	N.A.	37588	0.852	0.355	0	1	N.A.

Data sources: the DB1B, AOTP and T100 databases form the US Bureau of Transportation Statistics (BTS) and other data are from divers sources.

Table 3. Internalization of congestion cost conditional on airport load

	(1)	(2)	(3)
Dep. Var.		lnFare	
LnPassenger_a_15	-0.0204	-0.119***	
	(0.0277)	(0.0299)	
LnDelay_a_15	-0.398***	-0.575***	
	(0.123)	(0.136)	
LnPassenger_a_15 x LnDelay_a_15	0.0348***	0.0498***	
	(0.0105)	(0.0114)	
HHI_a_15	-0.111	-0.0862	
	(0.105)	(0.114)	
LnPassenger_m_15		0.151***	
		(0.0113)	
LnDelay_m_15		0.0148	
		(0.0215)	
LnPassenger_m_15 x LnDelay_m_15		-0.00495	
		(0.00438)	
HHI_m_15		-0.121***	
		(0.0452)	
LnPassenger_a_14			-0.0605**
			(0.0261)
LnDelay_a_14			-0.350***
			(0.127)
LnPassenger_a_14 x LnDelay_a_14			0.0274***
			(0.0101)
HHI_a_14			-0.0332
			(0.119)
LnPassenger_m_14			0.0887***
			(0.0121)
LnDelay_m_14			-0.00380
			(0.0235)
LnPassenger_m_14 x LnDelay_m_14			0.000782
			(0.00462)
HHI_m_14			0.185***
			(0.0417)
Hub	0.366***	0.133***	0.204***
	(0.0187)	(0.0198)	(0.0320)
Constant	6.049***	6.760***	6.162***
	(0.325)	(0.363)	(0.321)
Airline FE	Y	Y	Y
Season FE	Y	Y	Y
Market FE	Y	Y	Y
Control for market quality effects	N	Y	Y
Lagged by one year	N	N	Y
Observations	36,789	32,394	20,504
R-squared	0.452	0.477	0.535

Note: This table presents the estimation results of model (5)-(7). Column 1 is the result of model (5). Column 2 is the results of model (6). Column 3 is the results of model (7). Slot controlled airports, i.e., John F. Kennedy International Airport (JFK), LaGuardia Airport (LGA) and Ronald Reagan National Airport (DCA) are excluded from the sample and the airline fixed effect, season fixed effect and market fixed effect are controlled for in all models. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4. Internalization of congestion cost by carrier type

	(1)	(2)	(3)	(4)	(5)	(6)
	Low cost airlines			Full service airlines		
Dep. Var.	lnFare					
LnPassenger_a_15	0.0398	-0.0233		-0.0406	-0.137***	
	(0.0377)	(0.0526)		(0.0316)	(0.0330)	
LnDelay_a_15	0.101	-0.175		-0.505***	-0.653***	
	(0.123)	(0.198)		(0.143)	(0.150)	
LnPassenger_a_15 x LnDelay_a_15	-0.0110	0.00833		0.0436***	0.0564***	
	(0.0119)	(0.0177)		(0.0120)	(0.0125)	
HHI_a_15	-0.330***	-0.599**		-0.0905	-0.0805	
	(0.0847)	(0.276)		(0.121)	(0.119)	
LnPassenger_m_15		0.0183			0.153***	
		(0.0306)			(0.0119)	
LnDelay_m_15		0.0277			0.00568	
		(0.0661)			(0.0222)	
LnPassenger_m_15 x LnDelay_m_15		-0.00352			-0.00235	
		(0.0117)			(0.00462)	
HHI_m_15		-0.139*			-0.115**	
		(0.0783)			(0.0475)	
LnPassenger_a_14			0.0445			-0.0714**
			(0.0628)			(0.0290)
LnDelay_a_14			0.177			-0.402***
			(0.254)			(0.140)
LnPassenger_a_14 x LnDelay_a_14			-0.0190			0.0313***
			(0.0233)			(0.0112)
HHI_a_14			-0.196			-0.0371
			(0.262)			(0.122)
LnPassenger_m_14			-0.0338			0.0946***
			(0.0345)			(0.0126)
LnDelay_m_14			-0.0451			-0.00220
			(0.0601)			(0.0244)
LnPassenger_m_14 x LnDelay_m_14			0.0111			0.000520
			(0.0122)			(0.00482)
HHI_m_14			-0.150*			0.189***
			(0.0886)			(0.0431)
Hub	0.0827*	0.0844*	0.899***	0.385***	0.107***	0.179***
	(0.0464)	(0.0453)	(0.0705)	(0.0222)	(0.0239)	(0.0374)
Constant	4.571***	5.496***	4.236***	6.295***	6.967***	6.270***
	(0.398)	(0.617)	(0.712)	(0.377)	(0.399)	(0.354)
Airline FE	Y	Y	Y	Y	Y	Y
Season FE	Y	Y	Y	Y	Y	Y
Market FE	Y	Y	Y	Y	Y	Y
Control for market quality effects	N	Y	Y	N	Y	Y
Lagged by one year	N	N	Y	N	N	Y
Observations	3,703	2,558	1,175	33,086	29,836	19,329
R-squared	0.908	0.912	0.933	0.354	0.409	0.487

Note: This table presents estimation results using subsamples based on airlines' type. Column 1-3 are results for low cost airlines, i.e., Allegiant Air (G4), Frontier Airlines (F9), Spirit Airlines (NK), Sun Country Airlines (SY), Virgin America (VX). Column 4-6 are results for other full service airlines. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 5. Robustness check with IV estimation

	(1)	(2)	(3)
	Full sample	Low-cost airlines	Full service airlines
Dep. Var.	lnFare		
LnPassenger_a_14	-3.462**	-4.397	-3.665**
	(1.706)	(3.957)	(1.793)
LnDelay_a_14	-12.40**	-16.90	-12.89**
	(5.844)	(15.30)	(6.008)
LnPassenger_a_14 x LnDelay_a_14	1.362**	1.654	1.427**
	(0.659)	(1.488)	(0.686)
HHI_a_14	2.472**	-0.991	2.852**
	(1.252)	(0.758)	(1.438)
LnPassenger_m_14	-0.119	2.008	0.260
	(0.864)	(1.772)	(0.684)
LnDelay_m_14	1.112	3.448	1.184
	(1.374)	(2.933)	(1.229)
LnPassenger_m_14 x LnDelay_m_14	0.101	-0.763	-0.0537
	(0.381)	(0.671)	(0.305)
HHI_m_14	0.873***	0.0526	0.603***
	(0.332)	(0.204)	(0.218)
Hub	0.362***	0.334*	0.0600
	(0.111)	(0.197)	(0.139)
Lndistance	0.0596	0.466***	0.157**
	(0.106)	(0.0714)	(0.0713)
Constant	32.60**	39.08	33.43**
	(16.20)	(34.43)	(16.38)
Airline FE	Y	Y	Y
Season FE	Y	Y	Y
Market FE	N	N	N
Control for market quality effects	Y	Y	Y
Lagged by one year	Y	Y	Y
IV estimation	Y	Y	Y
Observations	20,504	1,175	19,329
R-squared	0.9041	0.9784	0.9217

Note: This table presents robustness check using IV estimation. Column 1 is results of full sample. Column 2 is results of low-cost airlines, i.e., Allegiant Air (G4), Frontier Airlines (F9), Spirit Airlines (NK), Sun Country Airlines (SY), Virgin America (VX). Column 3 is results of full service airlines. Slot controlled airports, i.e., John F. Kennedy International Airport (JFK), LaGuardia Airport (LGA) and Ronald Reagan National Airport (DCA) are excluded from the sample. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6. Robustness check with alternative measure of congestion

	(1)	(2)	(3)
	Full sample	Low-cost airlines	Full-service airlines
Dep. Var.		lnFare	
LnPassenger_a_14	-0.454***	-0.577	-0.529***
	(0.153)	(5.692)	(0.184)
LnUtilization_a_14	-15.57**	-22.51	-18.96**
	(6.245)	(226.9)	(7.817)
LnPassenger_a_14 x LnUtilization_a_14	1.450***	2.151	1.686***
	(0.509)	(20.92)	(0.615)
HHI_a_14	-0.509***	0.0174	-0.487***
	(0.137)	(3.292)	(0.135)
LnPassenger_m_14	0.215*	-0.992	0.123
	(0.128)	(15.81)	(0.124)
LnUtilization_m_14	8.058**	-29.77	7.516**
	(3.253)	(401.9)	(3.184)
LnPassenger_m_14 x LnUtilization_m_14	-0.665	4.100	-0.343
	(0.454)	(64.26)	(0.434)
HHI_m_14	0.661***	-0.414	0.697***
	(0.102)	(4.930)	(0.107)
Hub	0.506***	0.561	0.512***
	(0.0724)	(0.517)	(0.0761)
Lndistance	0.271***	0.607	0.252***
	(0.0153)	(1.885)	(0.0173)
Constant	5.689***	14.74	6.891***
	(1.681)	(37.00)	(1.993)
Airline FE	Y	Y	Y
Season FE	Y	Y	Y
Market FE	N	N	N
Control for market quality effects	Y	Y	Y
Lagged by one year	Y	Y	Y
IV estimation	Y	Y	Y
Observations	6,246	705	5,541
R-squared	0.9849	0.9833	0.9828

Note: This table presents robustness check using airport utilization rate as measurement of congestion. Column 1 is results of full sample. Column 2 is results of low-cost airlines, i.e., Allegiant Air (G4), Frontier Airlines (F9), Spirit Airlines (NK), Sun Country Airlines (SY), Virgin America (VX). Column 3 is results of other full-service airlines. Slot controlled airports, i.e., John F. Kennedy International Airport (JFK), LaGuardia Airport (LGA) and Ronald Reagan National Airport (DCA) are excluded from the sample. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7. Robustness check with non-hub and hub flights

	(1)	(2)	(3)	(4)	(5)	(6)
		Non-hub flights			Hub flights	
Dep. Var.			lnFare			
LnPassenger_a_15	0.0256	-0.117***		-0.00740	-0.0427	
	(0.0337)	(0.0372)		(0.0500)	(0.0526)	
LnDelay_a_15	-0.262*	-0.593***		-0.170	-0.183	
	(0.143)	(0.161)		(0.240)	(0.253)	
LnPassenger_a_15 x LnDelay_a_15	0.0234*	0.0525***		0.0252*	0.0369*	
	(0.0125)	(0.0138)		-0.0129	(0.0198)	
HHI_a_15	-0.0790	-0.0505		0.0191	0.155	
	(0.117)	(0.132)		(0.235)	(0.245)	
LnPassenger_m_15		0.142***			0.188***	
		(0.0125)			(0.0313)	
LnDelay_m_15		-0.00400			0.109*	
		(0.0233)			(0.0610)	
LnPassenger_m_15 x LnDelay_m_15		-0.000998			-0.0206*	
		(0.00481)			(0.0119)	
HHI_m_15		-0.133**			-0.0613	
		(0.0520)			(0.0731)	
LnPassenger_a_14			-0.0511			-0.0655*
			(0.0369)			(0.0353)
LnDelay_a_14			-0.348**			-0.285*
			(0.174)			(0.168)
LnPassenger_a_14 x LnDelay_a_14			0.0269*			0.0251*
			(0.0141)			(0.0132)
HHI_a_14			-0.0390			-0.00688
			(0.142)			(0.154)
LnPassenger_m_14			0.0863***			0.101***
			(0.0142)			(0.0330)
LnDelay_m_14			-0.00193			0.0134
			(0.0265)			(0.0631)
LnPassenger_m_14 x LnDelay_m_14			-0.000388			-0.00280
			(0.00528)			(0.0124)
HHI_m_14			0.192***			0.0730**
			(0.0532)			(0.0371)
Constant	5.481***	6.744***	6.059***	5.982***	5.577***	6.213***
	(0.386)	(0.442)	(0.446)	(0.607)	(0.654)	(0.453)
Airline FE	Y	Y	Y	Y	Y	Y
Season FE	Y	Y	Y	Y	Y	Y
Market FE	Y	Y	Y	Y	Y	Y
Control for market quality effects	N	Y	Y	N	Y	Y
Lagged by one year	N	N	Y	N	N	Y
Observations	28,999	24,827	15,575	7,790	7,567	4,929
R-squared	0.452	0.467	0.503	0.724	0.746	0.842

Note: This table presents estimation results using subsamples based on flight's type. Column 1-3 are results for flights with no hub airport. Column 4-6 are results for flights with at least one endpoint hub airport. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1