A Price for Delays: Price-Quality Competition in the US Airline Industry

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Abstract

This paper assesses effects of service quality competition, in terms of delays, in the US airline industry. We utilize delays along a route to evaluate the effect of endogenous (i.e., carrier) and exogenous (i.e., weather) factors on fares. In this study, we determine that while both endogenous and exogenous delays have a rather strong effect on ticket prices, additional exogenous delays have a greater effect on airfares. 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. Thus, our results indicate that airlines have incentives to reduce delays, but are not always penalized by passengers for delays that are within their control.

Keywords: Air traffic delays; service quality; hub airports; airport congestion

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1. Introduction

In recent years, airline flight delay performance has been receiving attention from the media, passengers, as well as the government. For instance, 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, the law passed in 2009 in the USA, known as the Passenger Bill of Rights, provides for substantial financial penalties to the airlines for keeping passengers in the 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[2].

Airline reliability is an observable measure of service quality, which can affect passenger demand for the airlines' services. A question we can then ask is whether passengers are imposing their own penalties through lower fares on delay prone routes. This paper examines the fare penalty for delay prone flights, and in the process makes three contributions to the economics literature. First, our estimation approach allows us to shed light on the price effects of endogenous versus exogenous service quality factors. Second, we approach the internalization of hub congestion issue. Our third aim is to bridge the existing literature gap between the product quality and airport congestion literatures by analyzing congestion in the context of the price – service quality relationship.

The hypothesis of direct relationship between delays and airfares derives quite straightforwardly from a simple profit-maximization problem of an airline choosing price and frequency of service,

[2] The maximum penalty that could be imposed is $27,500 for each stranded passenger.

in a model of vertical product differentiation, where product quality is defined as the product of frequency and service reliability. We take this hypothesis to the data by combining the airline price dataset (DB1B) with the delay data at the airline-airport-level. Our estimation methodology is airport-pair-market fixed effects, with controls for seasonal, airline, and connecting-airport-specific heterogeneity. Potentially endogenous market share variable is instrumented as proposed by Borenstein and Rose (1994). Three different delay measures are used: weather delays (which are out of the control of carriers), carrier delays (which is in the control of carriers), and total delays along the route. Of these, carrier delays and total delays are potentially endogenous. We use average delays at carrier's other hubs, weather delays, and average temperature at the hub airport as instruments.

Presence of the hub reliability premium, as far as carrier delays are concerned, is most clearly visible on those markets, where passengers have an available non-stop alternative, and is generally more pronounced at the upper end of the price distribution. Thus, while travelers switch to more reliable hubs when a non-stop alternative is present, resulting in lower airfares; there is less evidence that higher delays at hub airports consistently affect passengers whose only travel alternative is flying through a different hub. Of the measures we have used, weather delays have the largest effect on fares, in terms of magnitude. For instance, for the sub-sample of markets with an available non-stop alternative, an extra minute of weather delay increases average airfare by $4.46 (1.8%), and high fare goes up by $9.50 (2.1%). Interestingly, carrier delays do not affect airfares on those markets, where passengers do not have a non-stop flight alternative. However, quantitatively one extra minute of carrier delay is about as costly as a minute of weather delay on routes where non-stop alternatives are available. The size of the effect of total delays on the airfares ranges from $0.96 to $2.61 drop in price per additional minute of delay. This suggests that passengers penalize carriers more for exogenous factors, which are more observable, than endogenous factors, all else being equal.

Our results have implications for understanding of both the airlines' incentives, and effects of policies related to airport congestion. With respect to the former, it appears the airlines do have incentives for making an effort to reduce delays at their hubs; they are not, however, penalized for delays by passengers in markets where traveling non-stop is not a viable option. This result gives us some hope that the hub carriers do have an incentive to internalize hub congestion, as supposed by Brueckner (2002), and Mayer and Sinai (2003). Regarding airport congestion policies, it appears that lower delays at the hub airports will increase average airfares for one-stop trips by at most two percent. The airlines also should note that by choosing a hub in an area prone to weather delays, they are limiting their ability to charge higher fares to price insensitive passengers.

The paper is organized in the following way. Section 2 reviews the relevant literature. This is followed by a theoretical model to motivate the empirical work. Section 4 provides a description of the data, while Section 5 discusses hypothesis and methodology. Section 6 presents and discusses the empirical results, and the last section offers some concluding remarks.

2. Relevant Literature

While the impact of price effects on service quality factors is well documented, the effect of endogenous versus exogenous service quality factors on price is not as well studied. Reitman (1991) suggests that prices dominate a firm's choice of service quality, while Metrick and Zeckhauser (1998) show that price being equal, high service quality results in greater sales quantities than for lower quality products. Similar to the situation in the airline industry, where weather delay is somewhat predictable *ex ante* while carrier delay is not, Dinlersoz and Li (2006) suggest that price differences due to observable characteristics of product quality is a result of imperfect consumer information. We can generally claim that our study provides the first targeted investigation of the differences in price effects of exogenous versus endogenous quality characteristics.

Taking a quick look at the empirical investigation of air traffic delays, we can see that most of the papers in this literature deal with determinants rather than effects of delays. Notably, Mazzeo (2003) finds that there are shorter and fewer flight delays on routes and at airports with more competition. Lee and Rupp (2007) reported impact of pilots' wage reduction on airport delays, attributing this relationship to the pilots' effort level. Prince and Simon (2010) show that delays are positively related to the level of multimarket contact between airlines.

Up to now, the only other paper that examines price effects of delays is Forbes (2008), which studies the relationship between air traffic delays and prices at New York's LaGuardia airport. That paper finds that an additional minute of air traffic delays leads to $1.42 average drop in prices; and that the relationship between delays and airfares is stronger for more competitive routes. The latter conclusion is supported by our data – the relationship between airfares and delays is more robust in the sample of markets, where non-stop flight alternatives are available. Yet, we also discover that the response of prices to delays depends on the source of delays. Interestingly, while the scope of our study is wider than that of Forbes'; our estimate of the effect of an extra minute of total delay on average price is remarkably close to that obtained by Forbes.

One particularly important issue related to airport congestion is relationship between airport concentration and delays, relating to Brueckner's (2002) theoretical argument that dominant airlines will have incentives to self-internalize airport congestion. On the other hand, Daniel (1995) and Daniel and Harback (2008) suggest that competitive pressure exerted by fringe carriers will eliminate the dominant airlines' incentive to self-internalize congestion externality. Brueckner and Van Dender (2008) try to reach a consensus in the internalization debate showing that some competitive scenarios lead to self-internalization, while others do not.

Empirical research on self-internalization issue has not yet reached consensus. Mayer and Sinai (2003) demonstrate that, even though delays at hub airports are longer than at non-hub gateways; increasing airport concentration does lead to lower delays. Rupp (2009) reversed Mayer and Sinai's findings, using a different measure of delays. More recent evidence in favor of the congestion internalization hypothesis comes from Ater (2009). Thus, empirical studies of self-internalization issue to date have focused on relationship between airport concentration and delays. Our study takes a different approach. We effectively ask a simple question: "Do market forces punish hub operators for delays at their hubs?" An affirmative answer to this question points us towards a previously unexplored mechanism for possible self-internalization of airport congestion externality.

Also relevant to this paper are theoretical and empirical studies examining airlines' choice of frequency of service. Brueckner (2004) is the first model of the airline's choice between hub-and-spoke and point-to-point networks, which incorporates frequency of service. Brueckner and Flores-Fillol (2007) offer a model of scheduling competition, with two airlines competing in price and frequency. Flores-Fillol (2010) models frequency choice of an operator of the congestion-prone hub airport. Our model is admittedly simpler than those developed in the above-cited papers, as we abstract from the network considerations. On the empirical side, Pai (2010) offers a general examination of determinants of aircraft size and frequency choices in the

U.S. airline industry. Bilotkach et al. (2010), focusing primarily on the relationship between the frequency choice and distance, offer an analysis of the frequency choice by the airlines on a set of European markets.

3. A Model of Price-Reliability Relationship

This section establishes the link between hub reliability and airfares, considering a simple model of a monopoly airline choosing price and frequency of service. We arrive at quite an intuitive result of a direct relationship between higher airport reliability and price, mirroring Stiglitz (1987) assertion that "…in standard economic theory, higher quality items will sell at higher prices."

Consider a traveler contemplating a trip between points A and B. Suppose the traveler's indirect utility takes the form:

$$U = -p + \alpha\pi f \tag{1}$$

Where p is the airfare; f represents frequency of service; and π is the measure of airline's reliability of service. One can think of π as the probability of flight departing on-time, or of making a connection at the hub. Note that π is assumed to be exogenous. Then we can think of πf as the measure of the airline's quality of service: both higher frequency and better reliability of service reduce expected schedule delay. The term α then represents passenger's willingness to pay for quality. That is, we have a simple vertical product differentiation model. As is typical for models of this kind, we will differentiate passengers by their willingness to pay for quality by assuming uniform distribution of α on $[0,1]$ interval. Finally, we suppose that only passengers that attain non-negative indirect utility actually travel. This means that only passengers with $\tilde{\alpha} \geq \frac{p}{\pi f}$ will undertake the trip. The demand relationship then obtains trivially as:

$$q = \int_{\tilde{\alpha}}^{1} d\alpha = 1 - \frac{p}{\pi f} \tag{2}$$

Note that this demand function responds positively to increase in both frequency and reliability – when value of either of the two variables increases, demand becomes less responsive to price.

On the cost side, we assume decreasing returns to frequency: specifically, the airline's cost function is $c(f) = cf^2$. We effectively assume that the airline divides total traffic equally between aircraft of the same capacity, and that aircraft capacity itself is flexible. Such assumptions are not uncommon in models of airlines' frequency choice: decreasing returns to frequency of service are usually justified by the impact of increasing congestion as the airline adds flights to its schedule. In general, we need decreasing returns to frequency to ensure a non-negative value for this choice variable obtains in the solution to our profit-maximization problem.

$$\Pi(p, f) = p\left(1 - \frac{p}{\pi f}\right) - cf^2 \tag{3}$$

The first-order conditions for this profit-maximization problem are:

$$\frac{\partial \Pi}{\partial p} = 1 - \frac{2p}{\pi f} = 0 \tag{4}$$

$$\frac{\partial \Pi}{\partial f} = \frac{p^2}{\pi f^2} - 2cf = 0 \tag{5}$$

A quick look at the above conditions is sufficient to observe that the second-order conditions will be clearly satisfied. To find the closed-form solution of this problem, we first rearrange the above first-order conditions to:

$$\begin{cases} \pi f - 2p = 0 \\ p^2 - 2c\pi f^3 = 0 \end{cases} \tag{6}$$

From the first-order condition for price, it follows that $p = \frac{\pi f}{2}$; substituting this into the first-order condition for frequency, we obtain:

$$\frac{\pi^2 f^2}{4} - 2c\pi f^3 = 0 \tag{7}$$

$$\frac{\pi}{4} - 2cf = 0 \tag{8}$$

From the above expression, profit-maximizing price and frequency of service obtain trivially as:

$$f^* = \frac{\pi}{8c};\;\; p^* = \frac{\pi^2}{16c} \tag{9}$$

We can clearly see that both price-maximizing airfare and frequency of service positively and directly depend on the reliability of service. A seemingly counterintuitive negative relationship between profit-maximizing price and the cost parameter can be easily reconciled once we recognize that increase in c leads to the airline choosing lower frequency, which in turn reduces demand for travel, forcing the airline to reduce its price.

Of course, one deficiency of our simple modeling exercise above is that reliability is itself not assumed to be the function of frequency of service; whereas delays in real life do become more likely in more congested airports and airspace. One way to modify our model to account for this clearly realistic feature is to assume

$$\pi(f) = 1 - \pi_0 f \tag{10}$$

Where π_0 represents a marginal decline in service reliability as the airline adds an extra flight to its schedule. To ensure that in equilibrium an extra flight still reduces price sensitivity of travelers, we need $\pi_0 < 2c$. The airline's profit function now changes to:

$$\Pi(p,f) = p\left(1 - \frac{p}{f - \pi_0 f^2}\right) - cf^2 \quad (11)$$

And the corresponding first-order conditions become:

$$\frac{\partial \Pi}{\partial p} = 1 - \frac{2p}{f - \pi_0 f^2} = 0 \quad (12)$$

$$\frac{\partial \Pi}{\partial f} = \frac{p^2}{(f - \pi_0 f^2)^2}(1 - 2\pi_0 f) - 2cf = 0 \quad (13)$$

From the first-order condition for price, we obtain $p = \frac{1}{2}(f - \pi_0 f^2)$; substituting this into the first-order condition for frequency of service simplifies the latter to:

$$\frac{1}{4}(1 - 2\pi_0 f) - 2cf = 0 \quad (14)$$

After this, we can easily solve for profit-maximizing price and frequency of service:

$$f^* = \frac{1}{8c + 2\pi_0};\ \ p^* = \frac{8c + \pi_0}{2(8c + 2\pi_0)^2} \quad (15)$$

We can then consider comparative statics for profit-maximizing price and frequency with respect to changes in the marginal effect of an extra flight on service reliability (i.e., changes in π_0). An increase in π_0 (similar to a decline in general reliability level) clearly decreases profit-maximizing service frequency. Effect of π_0 on profit-maximizing price may not be immediately obvious; however, a simple differentiation exercise (which we omit here as an unnecessary distraction) clearly shows that an increase in π_0 indeed decreases the price.

As a final step, we will return to the original model to address the issue of exogenous versus endogenous reliability. Now, let π denote the exogenous reliability level; and we will allow the airline to increase this level by π_e (so that the total reliability is $\pi + \pi_e$), at the cost of $c_\pi \pi_e^2$ (as with frequency, we have decreasing returns to reliability). The airline's profit function is then given by the following expression (note that the carrier now chooses not only price and quality, but also the effort to be invested into increasing its reliability of service):

$$\Pi(p,f,\pi_e) = p\left(1 - \frac{p}{(\pi+\pi_e)f}\right) - cf^2 - c_\pi \pi_e^2 \tag{16}$$

The first-order conditions are:

$$\frac{\partial \Pi}{\partial p} = 1 - \frac{2p}{(\pi+\pi_e)f} = 0 \tag{17}$$

$$\frac{\partial \Pi}{\partial f} = \frac{p^2}{(\pi+\pi_e)f^2} - 2cf = 0 \tag{18}$$

$$\frac{\partial \Pi}{\partial \pi_e} = \frac{p^2}{(\pi+\pi_e)^2 f} - 2c_\pi \pi_e = 0 \tag{19}$$

The closed-form solutions for the three choice variables are found as before – by substituting expression for price as the function of other variables from the first of the three conditions above into the other two, and solving the resulting system of two equations in two unknowns. Specifically, we find the following expressions for the profit-maximizing price, frequency, and reliability effort:

$$p^* = \frac{256c\pi^2 c_e^2}{(64cc_e-1)^2}; f^* = \frac{32\pi c_e}{64cc_e-1}; \pi_e^* = \frac{\pi}{64cc_e-1} \tag{20}$$

A very interesting implication of the above solution is that profit-maximizing effort to increase service reliability appears to be positively related to the endogenous reliability level. To put this in perspective, it appears that the airline will be more willing to invest into better service quality in airports with better underlying weather conditions, other things equal. The puzzle is however solved once we come back to our original model and realize that when we plug the profit-maximizing price and frequency back into the profit function, the value of the airline's profit comes out as $\frac{\pi^2}{6c^2}(2-c)$; that is, there is an increasing marginal effect of reliability on profit. Therefore, the direct relationship between exogenous service reliability and effort to increase same is most probably specific to the functional form we assumed.

In summary, it is easy to theoretically establish the relationship between service reliability and price – the airline will charge more for a more reliable service in our simple model, and this result carries over to two simple extensions that we have attempted. The magnitude of the relevant effect is a purely empirical question, just as the question of the relative impact of delays that are purely exogenous to the airline versus those which the carrier has some control over.

4. Empirical Model and Data

4.1 Model Specification and Data Description

To conduct this study, the following model is estimated:

$$P_{ijk} = \alpha_{ij} + \beta D_{ijk} + \delta X_k + \phi Y_{ijk} + \gamma Z_{ijk} + \varepsilon_{ij} \qquad (21)$$

Where P_{ijk} represents the airfare charged by airline k on the route from airport *i* to endpoint *j*; α_{ij} are airport-pair-market fixed effects; D_{ijk} is our delay measure, calculated at the airline-route-connecting-airport level. Further, X_k represent carrier fixed effects; Y_{ijk} are connecting airport fixed effects; Z_{ijk} is the vector of control variables; and ε_{ij} represents the error term.

Data for the dependent variables, fares, are constructed from the US Department of Transportation (DOT) Origin and Destination Survey, databank DB1B. The DB1B is a 10 percent sample of actual itineraries, compiled quarterly by the US DOT. Each entry in the DB1B includes fare paid (net of taxes and fees), class of service[3], and detailed information on routing, including identity of airlines selling the ticket and operating each flight, distance traveled, and all intermediate airports visited. The destination of the trip is coded through the directional break in itinerary. This allows us to separately identify fares for a trip between different connecting points, for example Los Angeles to New York, via Chicago versus via Denver, our source for city-pair market, intra-route heterogeneity. We conduct this exercise for all quarters of 2005, to take advantage of, inter alia, potential seasonal variation in both airfares and air traffic delays.

From the DB1B, we calculate the natural logarithm of passenger weighted average airfare. We also hypothesize that the hub reliability premium may be higher at the high end of the price distribution than in the middle, as these would likely represent business travelers who are sensitive to travel delay. We thus need a representative airfare from the higher end of the price distribution. For such a measure, we use the passenger weighted mean plus one standard deviation of airfare.

Our delay measures are constructed from the Airline On-Time Performance dataset. Also published by the US Department of Transportation, this data is collected monthly and includes arrival and departure information for non-stop domestic US flights. Included in the dataset are departure and arrival delays, origin and destination airports, flight numbers, scheduled and actual departure and arrival times, cancelled or diverted flights, taxi-out and taxi-in times, air time, and non-stop distance. Beginning in October of 2003, the source of delay is attributed to one of six categories: carrier delay, weather delay, National Air System (NAS) delay, Security delay, and Late Aircraft delay. Carrier delay is all delay attributed to the carrier. Examples of such delays

[3] Services as classified as first unrestricted, first restricted, business unrestricted, business restricted, economy unrestricted, economy restricted.

are crew and gate scheduling issues, aircraft maintenance, and baggage handling. Once a flight leaves the gate, any subsequent delay to takeoff and landing is attributed to NAS delay. Therefore, NAS delay includes all delay attributed to Air Traffic Control issues, including airport congestion. Weather delay includes delays attributed to weather, including fog, snow, and wind that hamper airport operations. Security delay includes delays attributed to security issues, while Late Aircraft Delay is delay attributed to an airplane arriving late.

We construct three delay variables to determine whether endogenous and exogenous service quality factors have a greater impact on product price. We use the sum the total of all delays (carrier, weather, NAS, Security, and Late Aircraft) to gauge the aggregate relationship between fares and delays. Carrier delays evaluate the extent passengers punish tardy carriers for service quality factors that are within the airlines' control, while we use weather delay to measure the impact of service reliability, which is external to the carrier.

A noted shortcoming of the Ontime Performance dataset is that the source of the delay cannot be attributed to a particular airport. For example, San Francisco (SFO) is notorious for delays due to fog that forces the airport to limit the use of two of the four runways. A flight that involves SFO might be held on the ground at the destination to prevent air congestion at the destination. Since the delay measures cannot distinguish between the origin and destination, we sum the respective total, carrier, and weather delays on a route for a specific carrier. Thus, for instance, for a United Airlines flight from San Francisco to Boston via Denver, we will use the sum of United Airlines' delays at San Francisco, Denver, and Boston airports. Then, the differential in delays over different connecting points can be attributed to the respective connecting airports, and allows us to calculate a reliability premium.

Beyond fixed effects for the airlines and connecting airports, we utilize various variables to control for market heterogeneity. These variables include the national logarithm of distance flown, airline market share, the geometric average of population at the endpoint and connecting airports, and shares of households earning over $75,000 per year, averaged across origin, connecting, and destination areas. Distance and Market Share are derived from the DB1B database, while population data come from the 2000 Census. More details on the census data and their attribution to airports can be found in the Appendix.

4.2 Data Construction and Instrument Selection

From the DB1B databank, we selected roundtrip single-airline itineraries, connecting through the same city both ways and viewed airport-pair markets as directional, meaning that Los Angeles-New York market is regarded as separate from New York-Los Angeles route. Itineraries that include segments served by regional airlines were, for our purposes, assigned to their major carrier partners. To assign regional carriers to major airlines, annual 10K reports filed each year with the Securities and Exchange Commission by all major and regional airlines are analyzed to identify partnerships. Assignments are subsequently checked for accuracy by cross-checking regional carrier route maps and the schedules of their major carrier partners to ensure that the routes are properly assigned. The resulting assignments can be found in Table A.1 in the Appendix.

We further refined our dataset by selecting itineraries in which each segment was classified as restricted economy class; except for Southwest Airlines, which classifies all its tickets as `restricted first class`. The restricted economy classification is used most frequently in the dataset (over 85 percent of the time); and restricted economy fares appear to span the expected range of economy class fares rather well. In line with previous studies (e.g., Lee and Luengo-Prado, 2005), itineraries with fares less than 2 cents per mile (e.g., about $100 for a coast-to-coast roundtrip ticket) were dropped and we only chose those markets where 100 or more passengers were observed in the dataset over the year (markets with annual passenger traffic of over 1000 passengers, or about twenty passengers per week). Finally, we viewed airport-pair markets as directional, meaning that Los Angeles-New York market is regarded as separate from New York-Los Angeles route.

Selection and aggregation of the data resulted in the total of over 105,000 observations for about 5,000 non-directional airport-pair markets. Of those, about 3,700 markets also have available non-stop service. About two thirds of all observations are for the sub-sample of markets with available non-stop service. Summary statistics for the entire sample, as well as for sub-samples of airport-pair markets with and without available non-stop services are presented in Table 1.

The following facts stand out from Table 1. First, of the three delay measures we employed, weather delays appear to be the smallest in magnitude. At the same time, in relative terms weather delays are more dispersed, as measured by the ratio of standard deviation over mean, which is higher than one only for weather delays. Second, both weather delays and carrier delays are somewhat smaller for the sub-sample of markets with available non-stop services. Third, we note that an average itinerary in our sample represents a longer-haul flight (about 1,500 miles each way). But then, a stop along the way represents a substantial increase in travel time for shorter-haul itineraries, making flying non-stop or driving a much more attractive alternative. Finally, markets in the sub-sample with available non-stop services are on average shorter-haul, and represent trips between more populated areas, as compared to routes without available non-stop flights.

In addition to market-specific and airline-specific heterogeneity controlled by airport and airline fixed effectsm, we need to address the potential endogeneity of both control and key variables. Our control variable of market share is clearly endogenous. At the same time, two of our measures of delay can be endogenous as well. While weather delay is clearly outside of the airline's control, the carriers can respond to price shocks by taking steps that affect carrier delay and total delay. For instance, when prices of one-stop trips through a certain hub airport rise, the airline may decide to make its service more attractive and take actions, which will manifest in lower carrier and total delay. This means that carrier and total delays can be correlated with the error term.

To handle the problem of endogeneity of market share variable, we use the instrument proposed by Borenstein and Rose (1994), which basically is the airline's share of geometric average enplanements at the origin and destination airports. The calculation is as follows:

$$S_{ij}^{IV} = \frac{\sqrt{Pax_{i,j1}Pax_{i,j2}}}{\sum_k \sqrt{Pax_{k,j1}Pax_{k,j2}}}$$

Where $Pax_{i,j1}$ and $Pax_{i,j1}$ represent airline i's total passenger traffic at the origin ($j1$) and destination (*j2*) airports of market *j*. The numerator in the above expression is then the geometric average for airline i's total passenger enplanements at the two endpoints. The denominator is the sum of these geometric averages across all the airlines present at both airports. The correlation between market share and the instrument in our sample is 0.79, which means that the instrument is clearly not weak.

While we use a previously documented instrument for market share, we have to be a bit more creative for carrier and total delay. One obvious instrument to use is weather delay. Another weather variable correlated with both total and carrier delay, but not with the error term, is the temperature difference between the origin and the hub airports. Additionally, we have computed average delays at the airline-market level for other hubs through which the airline channels its traffic on a given route. In plain English, we use United Airlines' delays at Denver airport to instrument for the same carrier's delays at Chicago O'Hare, and vice versa. One shortcoming of this instrument is that we will retain observations only for those markets for which the airline channels its traffic via several hubs. Specifically, about 15 percent of observations are lost because of the use of this particular instrument.

5. Estimation Results

Results of our data analysis exercise are presented in Tables 2, 3, and 4. The only difference across the three tables is in the measure of delays used. Table 2 reports results for Total Delay; output for Carrier Delay is in Table 3; and effect of Weather Delay is reported in Table 4. Results are presented for both the entire sample, and for the two sub-samples we identified before (routes with and without available non-stop service). Finally, to test whether treating carrier and total delays as endogenous will change our results, Tables 2 and 3 report specifications treating delays as exogenous and as endogenous. Note that market share is treated as endogenous in all specifications reported in the above mentioned tables.

We use natural logarithm of average and high (average plus standard deviation) fare as dependent variables. White-robust standard errors are used to account for possible non-spherical disturbances.

Results of our data analysis present rather strong support for our hypothesized relationship between delays and airfares. Notably, weather delay affects price in all specifications. Carrier delay and total delay, on the other hand, have an effect only in regressions where they are treated as endogenous – note also that other parameter estimates do not change when we employ instruments for delay measures. At the same time, the relationship between carrier delay and prices is absent in the sub-sample of markets without available non-stop flight alternatives.

To translate price elasticities with respect to delay measures into more understandable terms, we computed marginal price effects of an extra minute of delay, at the sample mean values for both price and delays. Respective values are presented in Table 5. Note that relatively small price elasticities with respect to weather delay translate into relatively large values of marginal effects, as extra minute of weather delay corresponds to a substantial percentage change. In the same way, relatively large price elasticities with respect to total delay translate into smaller marginal effects.

Let us now provide an overview of our estimation results, focusing on different sub-samples and price measures we employed. In the discussion below, we will refer to results of specifications treating delay measures as endogenous, where applicable.

- Entire sample, average fare: across all markets included into our investigation, weather delay has the largest marginal effect on price. One additional minute of weather delay lowers average fare by $5.40 (1.65 percent of the sample mean fare); effect of an extra minute of carrier delay is exactly half as large. Observe that marginal effect of an extra minute of total delay is very close to that reported by Forbes (2008) in a study focusing on price-delays relationship at New York LaGuardia airport. In relative terms, one minute of total delay lowers mean fare by 0.44 percent.

- Entire sample, high fare: we observe much larger marginal effects at the upper tail of the price distribution, in both absolute and relative terms. One minute of weather delay lowers the price by as much as $9.43, which corresponds to 2.2 percent of the average high fare in our sample ($427.71). One extra minute of carrier delay decreases price by $5.07; whereas marginal effect of total delay is only $2.23 (corresponding to 0.5 percent of the average high fare).
- Markets with available non-stop service, average fare: carrier delay has the largest marginal effect in these specifications. It nearly doubles compared to the same estimate for the entire sample. This result implies that passengers tend to punish unpunctual carriers on those routes, where switching to non-stop services is a viable option.
- Markets with available non-stop service, high fare: as compared to same results for the entire sample, marginal effect of weather and total delay does not change, but marginal effect of the carrier delay again nearly doubles to $9.25 (about 2.3 percent of the mean high fare of $407.22).
- Markets without available non-stop services, average fare: here we observe the highest marginal effect of weather delay among specifications involving average fare as the dependent variable. One extra minute of weather delay decreases price by $6.55, or about two percent. Carrier delay does not have any statistically significant effect on prices; and effect of the total delay is quite small – one extra minute lowers the airfare by less than a dollar.
- Markets without available non-stop services, average fare: here, we do not observe any statistically meaningful relationship between carrier delay and price. Effect of total delay is

again very small. While extra minute of weather delay lowers the price by about 1.5 percent; this effect is only marginally significant.

Comparing results across the measures of delays, we see that delays exogenous to the airline generally have the larger effect on price. Compared to weather delay, effect of the carrier delay on airfares is modest for the entire sample, and non-existent for the sub-sample of markets without available non-stop services. Magnitudes of the marginal effects of weather and carrier delays are very similar for the sub-sample of markets with available non-stop services.

As far as control variables are concerned, there are no real surprises. Within sub-samples, the coefficients on control variables are quite stable, and do not depend much on the measure of delay used, as well as on whether delays are treated as exogenous or endogenous. Market share has an expected positive effect on prices. Distance has an expected negative effect on fares. Recall that within the airport-pair market fixed effects framework, higher distance corresponds to a more circuitous route. Population average affects fares positively, as expected, and more so at the higher end of price distribution. Negative effect of average high-earning households share is not as surprising as it seems at first glance. Recall that the average is taken across the origin, destination, and connecting airport's MSA, and within-cross-section variation in this variable comes from the connecting airports. Then, higher share of high-earning households in connecting airport's MSA will attract more non-stop traffic to that airport. This can send most connecting traffic within a cross-section through airports located in lower-income areas. On the other hand, airlines may charge higher fares going through hubs where origin-and-destination demand is high, as seats on flights to and from such hubs have higher option value. Thus, either a positive or a negative income-price relationship can be supported in the context of our data.

In summary, we find that delays at connecting airports do affect prices; the effect is somewhat stronger for the measure of delay, which is outside of the airlines' control. Carrier delay, or measure of quality of service which the carrier does have some control over, does not affect airfares as significantly. We can therefore suggest that carriers may only have limited incentive to do their part in reducing hub delays, as the market does not always penalize the airlines for the lack of punctuality.

6. Conclusions

Development of hub-and-spoke networks has been one of the most significant changes in the airline industry since deregulation. Hubs allow the airlines to reduce cost, and efficiently channel traffic within their networks. At the same time, hub airports often become congested and dominated by a single carrier. Airport dominance can lead to higher prices for flights to the hub; while congestion can result in air traffic delays. There is a debate in the literature as to whether dominant hub operators will have incentive to internalize the self-imposed congestion externality. One way to see if the market may provide such an incentive is to examine whether congestion at the hub will force the airlines to charge lower prices. This is one issue addressed in our study.

More generally, while relationship between service quality and prices is intuitive, in many industries some of the factors impacting quality are outside of the firm's control. Surprisingly, empirical studies that contrast price effects of exogenous and endogenous quality measures are absent. The airline industry provides an ideal setting for addressing this question.

We find that there is indeed an expected relationship between delays and airfares for travel through the delay-prone hub airports. At the same time, our data analysis suggests that airlines are not always penalized by the delays they have more direct control over; rather, the relationship we detected is the strongest for the weather delays, which are exogenous to the carriers. We consider the finding that carrier delays at hubs do not affect fares on markets, where passengers do not have a non-stop travel option, especially curious. It appears that on those markets the passengers are mostly concerned with how likely they are to get stuck in the hub because of the weather, and do not penalize the carriers for tardiness, which is under their control; despite the fact that carrier delays are on average about six times longer than weather delays. We believe that more detailed examination of the passengers' perception and impact of various types of delays is a fruitful topic for future research.

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Table 1 Descriptive Statistics of Variables

Variable	Entire Sample	Markets with Non-Stop Service	Markets without Non-Stop Service
Fare	\$326.99 (\$141.12)	\$315.28 (\$143.10)	\$350.37 (\$134.05)
Delays (minutes)			
Weather	0.69 (0.97)	0.70 (0.97)	0.69 (0.96)
Carrier	3.88 (2.72)	3.80 (2.65)	4.03 (2.85)
Total	16.17 (11.70)	16.54 (11.80)	15.46 (11.49)
Control variables			
Distance, miles, roundtrip	3,308 (1,600)	2,997 (1,454)	3,927 (1,696)
Market Share	0.16 (0.23)	0.16 (0.25)	0.18 (0.16)
Population Average	4,583,993 (2,258,110)	4,929,930 (2,354,863)	3,873,954 (1,852,917)
High Income Households Share, Average	0.26 (0.03)	0.26 (0.03)	0.26 (0.03)

Notes: The table reports means of respective variables. Standard deviations are in parentheses.

Table 2 Results for Total Delay

Variable	Entire sample				Markets with non-stop alternatives				Markets without non-stop alternatives			
	Treating delays as exogenous		Treating delays as endogenous		Treating delays as exogenous		Treating delays as endogenous		Treating delays as exogenous		Treating delays as endogenous	
	Average price	High price	Average price	High price	Average price	High price	Average price	High price	Average price	High price	Average price	High price
Constant	6.4703** (0.4073)	7.8106** (0.3397)	5.1697** (0.4095)	6.5692** (0.3154)	6.4379** (0.4194)	8.0681** (0.3653)	5.2097** (0.4049)	6.8078** (0.3219)	6.9240** (0.5737)	8.2241** (0.5195)	5.6644** (0.6546)	7.0244** (0.6390)
Log(Delay)	-0.0017 (0.0026)	-0.0046* (0.0028)	-0.0711** (0.0108)	-0.0845** (0.0108)	-0.0044 (0.0032)	-0.0090** (0.0037)	-0.0843** (0.0129)	-0.1064** (0.0134)	0.0021 (0.0032)	0.0028 (0.0035)	-0.0424** (0.0142)	-0.0395** (0.0157)
Market Share	0.2424** (0.0094)	0.2603** (0.0094)	0.2298** (0.0101)	0.2516** (0.0108)	0.2517** (0.0112)	0.2341** (0.0100)	0.2411** (0.0115)	0.2303** (0.0112)	0.1931** (0.0213)	0.4194** (0.0287)	0.1769** (0.0222)	0.3913** (0.0310)
Log(Distance)	-0.0082 (0.0082)	-0.2105** (0.0123)	-0.0086 (0.0078)	-0.2050** (0.0137)	-0.0059 (0.0081)	-0.2102** (0.0114)	-0.0081 (0.0088)	-0.2041** (0.0137)	-0.0292* (0.0172)	-0.1858** (0.0259)	-0.0232 (0.0167)	-0.1887** (0.0270)
Population Average	0.0132 (0.0088)	0.0477** (0.0080)	0.0493** (0.0091)	0.0833** (0.0083)	0.0092 (0.0094)	0.0397** (0.0087)	0.0464** (0.0096)	0.0788** (0.0090)	0.0194 (0.0138)	0.0331** (0.0141)	0.0485** (0.0160)	0.0622** (0.0167)
High-earning household share average	-0.1227** (0.0323)	-0.2397** (0.0274)	-0.1439** (0.0329)	-0.2672** (0.0287)	-0.1065** (0.0345)	-0.2351** (0.0300)	-0.1368** (0.0346	-0.2731** (0.0314)	-0.1708** (0.0464)	-0.2232** (0.0440)	-0.1742** (0.0482)	-0.2260** (0.0463)
Adjusted R-squared	0.3029	0.3199	0.2557	0.2686	0.2628	0.2806	0.2322	0.2414	0.3678	0.3583	0.2720	0.2714
Number of Observations	105267		88932		70272		59617		34995		29315	

Notes:

1. Dependent variable is the natural logarithm of passenger weighted mean fare (Average Price); or of passenger weighted mean fare plus standard deviation (High price)
2. Results reported here are for sub-sample of markets with more than 100 passengers per quarter. Results including thinner markets are available from the authors upon request.
3. Estimation technique used – 2SLS with airport-market-level fixed effects. Where delays are treated as endogenous, average delays at other hubs, weather delays, and temperature are used as instruments for delays.
4. Connecting airport dummies, quarter dummies, airline dummies, and connecting-airport-quarter interactions have been included into all regressions, but not reported.
5. White-robust standard errors are in parentheses.
6. Significance: ** - 5%; * - 10%

Table 3 Results for Carrier Delay

Variable	Entire sample				Markets with non-stop alternatives				Markets without non-stop alternatives			
	Treating delays as exogenous		Treating delays as endogenous		Treating delays as exogenous		Treating delays as endogenous		Treating delays as exogenous		Treating delays as endogenous	
	Average price	High price	Average price	High price	Average price	High price	Average price	High price	Average price	High price	Average price	High price
Constant	6.4171** (0.3980)	7.7748** (0.3403)	6.0806** (0.4022)	7.5294** (0.3144)	6.4331** (0.4140)	8.0775** (0.3641)	6.0761** (0.3939)	7.7696** (0.3108)	6.6730** (0.5412)	7.9470** (0.4927)	6.5475** (0.5850)	7.8077** (0.5714)
Log(Delay)	-0.0133** (0.0036)	8.64E-05 (0.0036)	-0.0320* (0.0181)	-0.0461** (0.0173)	-0.0170** (0.0046)	-0.0056 (0.0051)	-0.0619** (0.0215)	-0.0864** (0.0205)	-0.0093** (0.0045)	0.0084 (0.0054)	0.0379 (0.0344)	0.0505 (0.0447)
Market Share	0.2386** (0.0090)	0.2603** (0.0090)	0.2164** (0.0094)	0.2363** (0.0173)	0.2480** (0.0108)	0.2337** (0.0098)	0.2250** (0.0115)	0.2101** (0.0106)	0.1873** (0.0208)	0.4158** (0.0287)	0.1688** (0.0201)	0.3856** (0.0298)
Log(Distance)	-0.0070 (0.0079)	-0.2063** (0.0124)	-0.0077 (0.0080)	-0.2002** (0.0141)	-0.0061 (0.0078)	-0.2078** (0.0114)	-0.0073 (0.0087)	-0.1990** (0.0138)	-0.0241 (0.0173)	-0.1769** (0.0261)	-0.0208 (0.0168)	-0.1821** (0.0273)
Population Average	0.0159* (0.0087)	0.0471** (0.0082)	0.0266** (0.0094)	0.0589** (0.0087)	0.0118 (0.0095)	0.0396** (0.0088)	0.0276** (0.0096)	0.0580** (0.0086)	0.0237* (0.0133)	0.0350** (0.0138)	0.0189 (0.0154)	0.0325* (0.0180)
High-earning household share average	-0.1296** (0.0313)	-0.2380** (0.0263)	-0.1440** (0.0320)	-0.2692** (0.0286)	-0.1173** (0.0340)	-0.2386** (0.0296)	-0.1497** (0.0333)	-0.2921** (0.0313)	-0.1675** (0.0434)	-0.2115** (0.0426)	-0.1447** (0.0465)	-0.1902** (0.0492)
Adjusted R-squared	0.3073	0.3244	0.2652	0.2780	0.2647	0.2829	0.2420	0.2521	0.3746	0.3655	0.2746	0.2720
Number of Observations	105267		88932		70272		59617		34995		29315	

Notes:

1. Dependent variable is the natural logarithm of passenger weighted mean fare (Average Price); or of passenger weighted mean fare plus standard deviation (High price)
2. Results reported here are for sub-sample of markets with more than 100 passengers per quarter. Results including thinner markets are available from the authors upon request.
3. Estimation technique used – 2SLS with airport-market-level fixed effects. Where delays are treated as endogenous, average delays at other hubs, weather delays, and temperature are used as instruments for delays.
4. Connecting airport dummies, quarter dummies, airline dummies, and connecting-airport-quarter interactions have been included into all regressions, but not reported.
5. White-robust standard errors are in parentheses.
6. Significance: ** - 5%; * - 10%

Table 4 Results for Weather Delay

Variable	Entire sample		Markets with non-stop alternatives		Markets without non-stop alternatives	
	Average price	High price	Average price	High price	Average price	High price
Constant	6.4339** (0.4069)	7.7304** (0.3366)	6.4730** (0.4234)	8.0664** (0.3626)	6.6346** (0.5420)	7.8468** (0.4956)
Log(Delay)	-0.0114** (0.0031)	-0.0139** (0.0031)	-0.0099** (0.0041)	-0.0145** (0.0041)	-0.0129** (0.0050)	-0.0101* (0.0061)
Market Share	0.2391** (0.0089)	0.2592** (0.0090)	0.2490** (0.0108)	0.2332** (0.0097)	0.1866** (0.0207)	0.4138** (0.0284)
Log(Distance)	-0.0078 (0.0079)	-0.2065** (0.0124)	-0.0072 (0.0078)	-0.2084** (0.0114)	-0.0246 (0.0173)	-0.1770** (0.0262)
Population Average	0.0141 (0.0088)	0.0481** (0.0081)	0.0091 (0.0094)	0.0393** (0.0086)	0.0233* (0.0133)	0.0380** (0.0137)
High-earning household share average	-0.1238** (0.0311)	-0.2381** (0.0260)	-0.1101** (0.0336)	-0.2366** (0.0290)	-0.1626** (0.0436)	-0.2141** (0.0426)
Adjusted R-squared	0.3072	0.3246	0.2645	0.2830	0.3747	0.3657
Number of Observations	105267		70272		34995	

Notes:

1. Dependent variable is the natural logarithm of passenger weighted mean fare (Average Price); or of passenger weighted mean fare plus standard deviation (High price)
2. Estimation technique used – 2SLS with airport-market-level fixed effects.
3. Connecting airport dummies, quarter dummies, airline dummies, and connecting-airport-quarter interactions have been included into all regressions, but not reported.
4. White-robust standard errors are in parentheses.
5. Significance: ** - 5%; * - 10%

Table 5 Marginal Effect of One Minute of Delay

Measure of Delay	Entire Sample	Markets with Non-Stop Service	Markets without Non-Stop Service
Change in average fare			
Weather Delay	-$5.40	-$4.46	-$6.55
Carrier Delay	-$2.70^	-$5.13	$0.00
Total Delay	-$1.44	-$1.61	-$0.96
Change in high fare			
Weather Delay	-$9.43	-$9.50	-$7.09^
Carrier Delay	-$5.07	-$9.25	$0.00
Total Delay	-$2.23	-$2.61	-$1.19

Note: where the corresponding regression coefficient is statistically not significantly different from zero; we put zero for the value of change in price per extra minute of delay; ^ indicates that the underlying regression coefficient is significant at 10%, but not at 5% level. For Carrier Delay and Total Delay, the marginal effects have been computed based on the estimates from specifications, treating delays as endogenous.

Appendix

Table A.1 Assignment of Regional Carriers

Major Carrier	Regional Carrier
American Airlines (AA)	American Eagle* Executive Airlines* Regions Air Chautauqua Airlines Trans States
Alaska Airlines (AS)	Horizon Air*
Continental Airlines (CO)	ExpressJet Commutair Colgan Skywest
Delta Air Lines (DL)	ASA/ Atlantic Southeast Airlines* Comair* Skywest Chautauqua Airlines[a] Republic Freedom[b]
Northwest Airlines (NW)	Mesaba Airlines Express Airlines
United Airlines (UA)	Air Wisconsin[c] GoJet Shuttle America Trans States Skywest[d] Mesa Chautauqua Airlines Colgan[e]
US Airways (US)[f]	Air Wisconsin Chautauqua Airlines Mesa

Regional carriers that serve multiple majors are assigned based on hub identities.

Notes:

[a] Only routes involving cities in Florida and Raleigh-Durham (RDU)

[b] Only routes involving Orlando, FL (MCO)

[c] Only on routes involving Chicago O'hare (ORD) and Washington Dulles (IAD)

[d] Including routes involving Portland, OR (PDX), Medford, OR (MFR), and Eureka-Arcata, CA (ACV)

[e] Only routes involving Washington Dulles (IAD)

[f] The following airlines, which are observed in the database, are also assigned to US Airways: PSA Airlines, Piedmont, and America West

Demographic Variables

Demographic data for this analysis comes from the 2000 Census data gathered from the 2007 State and Metropolitan databook. Airports were assigned to a metropolitan statistical area (MSA) based on the name of the airport. Most airports identify themselves as serving a specific city, and therefore a matching MSA, making the assignment of census data unambiguous.

However, ambiguity arises in two special cases: (i) where one airport serves multiple MSAs, and (ii) where multiple airports serve a given MSA. In case (i), the population-weighted average of the demographic data for the relevant MSAs was computed. Affected airports were CAK, where the Akron, OH and Canton-Massillon, OH MSAs were combined; ELM, where the Corning, NY and Elmira, NY MSAs were combined; MAF, where the Midland, TX and Odessa, TX MSAs were combined; RDU, where the Raleigh and Durham, NC MSAs were combined. For the Hartford-Springfield International Airport, BDL, the airport was assigned to the Hartford, CT, MSA due to the longer distance to Springfield, MA.

In case (ii), the same MSA was assigned to each airport in the area, unless it was possible to assign a Metropolitan Division to the airport. For the Los Angeles MSA, Los Angeles International (LAX) was assigned to the Los Angeles Metropolitan Division and Orange County John Wayne (SNA) to the Santa Ana-Anaheim-Irvine Division. For the San Francisco Bay Area, San Francisco International (SFO) was assigned to the San Francisco-San Mateo-Redwood City Division, and Oakland International (OAK) to the Oakland-Fremont-Hayward Division. San Jose Mineta International (SJC) was assigned to the San Jose-Sunnyvale-Santa Clara, CA MSA. In the Chicago area, O'Hare (ORD) and Midway (MDW) were assigned to the Chicago MSA. For the New York City area, LaGuardia (LGA), John F. Kennedy (JFK), and Newark (EWR) were assigned to the New York-North New Jersey-Long Island MSA. Islip (ISP) and White Plains (HPN) were assigned to the Nassau-Suffolk and New York-White Plains Metropolitan Divisions, respectively.

Several airports do not fall into a MSA or could not be easily assigned to a Metropolitan Division in a large MSA, and for these cases, census data were gathered for the city in which airport is located. These airports are Traverse City, MI, Pasco, WA, Montrose, CO, Missoula, MT, Melbourne, FL, Jackson, WY, Helena, MT, Gunnison, CO, Bozeman, MT, Vail, CO, Kalispell, MT, Meridian, MS, Butte, MT, Hanover, NH Minot, ND, Harlingen, TX, Temple, TX, Cody, WY, Burbank, CA, Long Beach, CA, Palm Springs, CA, Aspen, CO, Durango, CO, Hayden, CO, Key West, FL, Marathon, FL, Brunswick, GA, Burlington, IA, Presque Isle, ME, Nantucket, MA. Due to the lack of available data, Martha's Vineyard and Hyannis, MA were assigned to their respective counties of Barnstable and Dukes.