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Do market-concentrated airports propagate more delays than less concentrated ones? A case study of selected U.S. airports

Tony Diana

Federal Aviation Administration, Washington, DC, United States

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A B S T R A C T

Airport congestion and widespread passenger discontent with airlines' poor on-time performance have recently led the Federal government to reduce peak-time operations at large airports such as Chicago O'Hare and New York John F. Kennedy. This paper proposes a methodology to compute delay propagation based on the discrete Fourier transform (DFT) at a sample of ten U.S. airports in summer 2000, 2007 and 2008. The sampled airports are different in terms of size, location and index of concentration.

In this research, a flight is considered to be late if it arrives more than fifteen minutes past its schedule. Delay propagation is defined as the hourly ratio of two amplitudes: the one of late arrivals at a sampled airport to that of late arrivals at the final destinations served from that same sampled airport. The purpose of this study is to determine whether delay propagation differs at market-concentrated airports from less concentrated ones. Based on nonparametric tests and proximity analysis, there is no clear evidence that market-concentrated airports are different from less concentrated ones in terms of propagated delays.

1. Introduction

Delay propagation is a timely issue: It is most likely to increase the social costs of delays by slowing the efficient flows of commodities and passengers through the National Airspace System (NAS).[1] To stem the rise in delays and resulting congestion, the Federal government implemented delay reduction initiatives such as caps at arrivals at Chicago O'Hare and reduced operations at peak times at JFK and EWR in 2008.

Table 1 provides the delays at the sampled and OEP 35[2] airports. It indicates that the average minutes of delays for all arrivals[3] declined 0.80 min in summer 2008 and increased 1.94 min in summer 2007 compared with summer 2000—one of the worst summers on record for delays. Furthermore, the average minutes of delays for delayed arrivals rose 5.82 min in summer 2007 and 0.41 min in summer 2008 compared with summer 2000.

Because airports form an interdependent network—called the NAS—delays accumulated at one airport may propagate to others in subsequent stages of a flight.[4] Several studies mentioned in the literature survey focused on the role of hubs[5] in absorbing delay propagation. Presumably, large network carriers can use their dominance at their 'fortress hub' to coordinate flight schedules and thus minimize the impact of turn time and passenger transfer delays.

This study takes a different perspective on the subject of delay propagation because it is based on frequency domain analysis. Delay propagation is measured as the ratio of the amplitude of delayed arrivals into and out of a given airport. If flights arrive more than fifteen minutes past their schedule, the delays may be construed as propagated. In fact, there is some evidence in the literature that schedules are likely to be padded (Hansen et al., 1998; Wu, 2005). Therefore, do airports in higher market-concentrated markets feature the same distribution of delay propagation

E-mail addresses: tonydiana1@verizon.net, tony.diana@faa.gov

[1] See 'Your Flights Has Been Delayed: Flight Delays Cost Passengers, Airlines, and the U.S. Economy Billions in 2007', U.S. Joint Economic Committee, May 2008.

[2] The OEP 35 airports account for about 75% of all the U.S. passenger enplanements.

[3] The Aviation Systems Performance Metrics (ASPM) provides airline and airport performance statistics (http://aspm.faa.gov). The delays for all arrivals are those one minute or more past the arrival schedule time. The delays for delayed arrivals are those greater than 15 min past the arrival schedule time.

[4] According to the Bureau of Transportation Statistics, 38.93% of all the reported delays by major U.S. carriers in June to August 2007 were attributed to late arriving aircraft compared with 35.49% during the same period of 2008.

[5] Large hubs are defined as the airports that handle 1% or more of total passenger boardings within the United States in the most current calendar year ending before the start of the current fiscal year. Medium hubs get less than 1% but more than 0.25% of the total passenger boardings. Small hubs handle at least 0.05% of the U.S. passenger boardings and less than 0.25%.

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Table 1
Aviation systems performance metrics: delays compared with schedules.

	Average minutes of delay for all arrivals (June–August)			Average minutes of delay for delayed arrivals (June–August)		
	2000	2007	2008	2000	2007	2008
ATL	16.46	22.11	18.20	53.56	63.33	66.80
BOS	25.63	22.30	22.34	60.95	61.17	66.31
DCA	15.01	19.43	14.72	53.27	61.94	61.29
IND	17.08	19.30	14.19	47.41	55.72	55.36
JFK	20.47	31.18	29.44	56.91	72.06	71.98
LGA	26.17	27.06	25.51	65.29	66.81	65.88
MCO	18.24	17.48	15.60	56.76	58.35	58.64
ORD	26.65	22.24	21.54	61.88	69.04	69.38
PDX	10.81	12.13	9.94	44.71	49.64	47.24
SAN	14.09	13.85	12.64	45.03	51.02	50.07
OEP 35	17.22	19.15	16.48	54.77	60.59	61.00

Source: ASPM, OAG.

as those in less concentrated ones? In this study, a market is considered to be concentrated if the Herfindahl–Hirschmann Index (HHI) is greater than 1800.

The next section will provide a brief overview of research in the area of delay propagation before detailing the research design and the results.

2. Research background

Quite a few studies have assessed delay propagation from a bottleneck and queuing model perspective. However, none has evaluated delay propagation from a frequency domain standpoint as in the present research.

According to Daniel (1995), dominant carriers were more likely to internalize self-imposed delays because they were capable of coordinating their arrival and departure banks. Based on bottleneck and queuing models, Daniel rejected the internalization hypothesis.

Bruekner (2002), Mayer and Sinai (2003) studied the relationship between airline dominance at an airport and the level of delays. The authors found that the level of delays decreased as airline dominance increased, other things being equal.

Wang et al. (2003) presented a simple analytic model that explicitly separated the controllable factors that influenced delays and propagation of delays in the NAS from those factors that were random variables in a given scenario. The controllable type of factor was called "fixed" and the random type of factor was referred to as "variable". A simple relationship existed among the fixed and variable factors that characterized NAS delay propagation. They showed how the model could be applied to better understand delay propagation from specific NAS airports, especially the effects of flight schedule parameters on measured delay. Recorded data from actual NAS operations were used to derive estimates on key model parameters and to show how delay characteristics varied among different airports.

Evans et al. (2004) analyzed the situation of traffic delays in convective weather. They identified the factors that adversely impacted the operations of airports in convective storms. Then, Evans et al. studied other effects such as delay ripples (knock-effect on subsequent flights and crews) and they proposed delay models that could be used to anticipate delays with reasonable reliability.

Bayen et al. (2005) derived a control theoretical model of sector-based air traffic flow. Their paper provided an improved method of estimating propagated delay and used these estimates to consider a version of the ground delay problem that took into account equipment and crew interactions. They started by developing expressions for propagated delay for various weather-inflicted scenarios. Then, they used the Delay Propagation model (PD) as a surrogate cost in the formulation of the assignment model to solve the ground delay problem. They achieved this by segregating all incoming and outgoing flights into three independent categories, based on how crew and equipment were split over the outgoing flight legs. An assignment model for the allocation of arrival slots to incoming flights was then developed. This formulation included cubic, quadratic and linear assignments. A solution methodology using a Simulated Annealing (SA) meta-heuristic was proposed. The model and its solution procedure were statistically tested for various ground delay instances. According to the authors, PD without accounting for equipment and crew interactions could result in poor delay estimates for aircraft. Overall delay could be well controlled by judicious slot assignments in a ground holding situation by taking these delay estimates into account.

Wu (2005) explored the inherent delays of airline schedules resulting from limited buffer times and stochastic disruptions in airline operations. The reliability of airline schedules was discussed and a set of measuring indices was developed to evaluate schedule reliability. It was found that significant gaps existed between the real operating delays, the inherent delays (from simulation) and the zero-delay scenario. Delay propagation and its impact on schedule reliability were also addressed. Results showed that airline schedules must consider the stochasticity in daily operations. Schedules may become robust and reliable, only if buffer times were embedded and designed properly in airline schedules.

According to Hansen and Hsiao (2005), the recent increase in flight delays in the U.S. domestic system was analyzed by estimating an econometric model of average daily delay that incorporated the effects of arrival queuing, convective weather, terminal weather conditions, seasonal effects, and secular effects (trends in delays not accounted for by other variables). From the estimation results it was possible to quantify some sources of higher delays in late 2003 and early 2004 and track changes in delays that were not attributable to major causal factors. Results suggested that when these factors were controlled for, delays decreased steadily from 2000 through early 2003, but that the trend reversed thereafter. Of the total delay increase between early 2003 and early 2004, half to two-thirds could be attributed to specific sources.

In the next section, we will define delay propagation and detail the methodology designed to measure the amplitude of propagation.

3. Methodology

3.1. *Definition of delay propagation*

According to Merriam Webster,[6] to propagate means (1) to cause to spread out and affect a greater number or greater area; (2) to transmit (as sound or light) through a medium. The notion of delay propagation can be related to the concept of wave propagation: Delays represent signals propagated through the NAS as the medium.

In this research, delay propagation is defined as the ratio of the amplitude of the delayed arrivals at a specific sampled airport (for instance ATL) to the delayed arrivals at all the destinations served from the same sampled airport (ATL in our case). The ratio is computed by local hour at the sampled airport. The arrival schedule is the performance benchmark since it represents airlines' commitment to deliver passengers by a given time. Because airlines are likely to pad their schedule in order to anticipate enroute and airport delays, any delayed arrival more than fifteen minutes can be construed as the result of propagation: It took extra time for an

[6] See http://www.merriam-webster.com.

airline to get to its destination despite the anticipated delays integrated into the schedule.

3.2. The sample of airports

This study used a sample of ten large U.S. airports (see Appendix 1 for the list and codes) whose on-time performance is tracked daily by the Aviation Systems Performance Metrics (ASPM). The Bureau of Transportation Statistics (BTS) reports delays and their causes only on a monthly basis for a sample of domestic flights operated by the largest U.S. air carriers.[7] BTS does not provide daily or hourly on-time performance, whereas ASPM does since it compiles ARINC's Out-Off-On-In as well as Enhanced Traffic Management System (ETMS) data every day.

The airports in the sample were selected on the basis of market concentration measured by the Herfindahl–Hirschmann Index (HHI).[8] The Herfindahl–Hirschmann Index (HHI) was derived from the schedule of seller carriers (including the mainline and regional airlines) published by the Official Airline Guide (OAG). The HHI is calculated by squaring the market share of each airline competing in the market and then summing the resulting numbers. For example, for a market consisting of four airlines with shares of thirty, thirty, twenty and twenty percent, the HHI is 2600 ($30^2+30^2+20^2+20^2=2600$). Markets whose HHI is between 1000 and 1800 points are considered to be moderately concentrated compared with those whose HHI is in excess of 1800 points. Table 2 features the HHIs for each sampled airport, by selected season.

The only change in the HHI among the sampled airports is JFK. According to the OAG, the market share of JetBlue at JFK (among domestic carriers serving domestic markets) was about 10% of the total domestic arrivals in summer 2000. It grew to 58% in summer 2007 and slightly went down to 50% in summer 2008.

Table 2
Hirschmann–Herfindahl index (June–August).

	2000	Concentrated	2007	Concentrated	2008	Concentrated
ATL	5429	Yes	4634	Yes	4725	Yes
BOS	1695	No	1343	No	1376	No
DCA	2303	Yes	2667	Yes	2363	Yes
IND	1266	No	1375	No	1406	No
JFK	1725	No	3886	Yes	3200	Yes
LGA	1800	No	1542	No	1576	No
MCO	1427	No	1473	No	1496	No
ORD	3934	Yes	4163	Yes	4035	Yes
PDX	1994	Yes	2445	Yes	2617	Yes
SAN	1973	Yes	2154	Yes	2350	Yes

Source: OAG.

3.3. The measurement of delay propagation

As propagated signals, delays are characterized by three key elements: magnitude (amplitude), cycles (phases) and velocity. As such, signals can be best analyzed in the frequency as opposed to the time domain.[9]

The Fourier transform is defined as

$$X(w) = \int_{-\infty}^{\infty} x(t)e^{-jwt}\,dt, \quad w \in (-\infty, \infty)$$

If N samples of the signal are taken at intervals Ts, the sampled values are $x(0)$, $x(T_k)$, $x(2T_k)$, …, $x[(N-1)T_k]$. They define the values of a discrete time signal denoted by x_n (see McMahon, 2006). The discrete Fourier transform (DFT) is characterized by the following function:

$$X_k = \sum_{n=0}^{N-1} x_n e^{-\frac{2\pi i}{N}kn}, \quad k = 0, \ldots, N-1$$

The DFT is appropriate for a continuous time signal of finite duration with one hour as the sampling period. Summer was selected since it usually represents the time of the year when airport operations and delays reach their peak. Since delayed flights were sampled by hour and by summer (from June 1 to August 31), the DFT allows the conversion of time domain into frequency domain outputs characterized by amplitudes and phases. The amplitude can be defined by the equation $A_i=((\mathrm{FFT_{real}})^2+(\mathrm{FFT_{imaginary}})^2)^{1/2}$ and the phase by $\theta_i=\arctan(\mathrm{FFT_{imaginary}}/\mathrm{FFT_{real}})$. FFT refers to Fast Fourier Transform. In this study, the minimum frequency was 0.067 and the Nyquist frequency 0.50.

The DFT algorithm provides the amplitudes and phases of delayed arrivals for summer 2000, 2007 and 2008. The amplitude represents the magnitude of propagation and it can be defined as the maximum displacement of the 'delay wave'. The amplitude represents a measure of propagation intensity. The phase corresponds to a point in the time of a cycle with reference to an arbitrary zero and is usually expressed as an angle. Bloomfield (2000) provides an excellent exposition of the application of Fourier analysis to time series.

Table 3 provides an example of how the hourly delay propagation ratios for ATL in summer 2008 were computed using DFT. The real, imaginary numbers, the amplitudes and phases were generated by the procedure SPECTRA in SAS (Fig. 1).

In the next section, we will examine whether the delay propagation ratios differ by airport and by season. Nonparametric tests were used since data were assumed not to have a normal distribution.

4. Findings

4.1. Nonparametric tests

Nonparametric tests are traditionally used to analyze data when there is no assumption of normal distribution. The Kruskal-Wallis test is suitable when comparing the mean ranks of more than two groups (i.e., summer 2000, 2007 and 2008) in order to determine whether or not they are different. It is an extension of the Mann–Whitney test primarily used for two groups.

The Kruskal-Wallis test assumes several conditions: (1) the random samples from each population are independent, (2) all the populations have the same distribution, and (3) the variances of the populations are the same. This was made possible by using the DFT

[7] BTS data cover all domestic nonstop flight segments flown by U.S. carriers with at least 1 percent of passenger revenues in the previous year.

[8] The Hirschmann–Herfindahl index is measured as follows

$$H = \sum_{i=1}^{N} s_i^2$$

with s_i being the market share of firm i in a given market and N representing the number of firms.

[9] French mathematicians such as D'Alembert in the 18th century and Fourier in the 19th century studied propagation in the respective areas of vibrating strings and heat conduction. Fourier showed that any function can be decomposed in terms of sinusoidal functions of different frequency. D'Alembert proposed a solution to the wave equation. It "was based on the observation that the general solution of $u_{tt}=c^2u_{xx}$ could be decomposed into the sum of two travelling waves, each travelling at speed c but in opposite directions" Knobel (2000, p. 77).

Table 3
Frequency domain analysis at Atlanta Hartsfield/Jackson International Airport (Summer 2008).

Local hour at ATL	UTC at ATL	Total delays for delayed arrivals	f	H_{re}	H_{im}	Amplitude	Phase
From all origins to ATL							
0700	1100	342	−0.4667	−53.1930	−14.9102	55.2432	−2.8683
0800	1200	622	−0.4000	10.4731	1.7909	10.6252	0.1694
0900	1300	446	−0.3333	−19.0680	29.2232	34.8939	2.1489
1000	1400	476	−0.2667	−65.2133	53.3386	84.2483	2.4560
1100	1500	484	−0.2000	−106.9180	−21.8771	109.1332	−2.9398
1200	1600	748	−0.1333	−46.2532	−113.9282	122.9594	−1.9565
1300	1700	783	−0.0667	−36.8944	−271.0619	273.5612	−1.7061
1400	1800	979	0.0000	976.0550	0.0000	976.0550	0.0000
1500	1900	1194	0.0667	−36.8944	271.0619	273.5612	1.7061
1600	2000	1134	0.1333	−46.2532	113.9282	122.9594	1.9565
1700	2100	1260	0.2000	−106.9180	21.8771	109.1332	2.9398
1800	2200	1156	0.2667	−65.2133	−53.3386	84.2483	−2.4560
1900	2300	1955	0.3333	−19.0680	−29.2232	34.8939	−2.1489
2000	0000	1885	0.4000	10.4731	−1.7909	10.6252	−0.1694
2100	0100	1179	0.4667	−53.1930	14.9102	55.2432	2.8683
At all destinations from ATL							
0700	1100	253	−0.4667	−12.8173	13.9109	18.9155	2.3153
0800	1200	393	−0.4000	−37.4100	−7.7818	38.2108	−2.9365
0900	1300	478	−0.3333	−44.8424	10.4151	46.0360	2.9134
1000	1400	439	−0.2667	−67.3900	−39.8186	78.2747	−2.6079
1100	1500	468	−0.2000	−42.6878	−61.5275	74.8858	−2.1773
1200	1600	455	−0.1333	−21.6067	−39.9433	45.4127	−2.0667
1300	1700	603	−0.0667	−38.0439	−206.5437	210.0182	−1.7529
1400	1800	814	0.0000	782.2794	0.0000	782.2794	0.0000
1500	1900	827	0.0667	−38.0439	206.5437	210.0182	1.7529
1600	2000	1149	0.1333	−21.6067	39.9433	45.4127	2.0667
1700	2100	1158	0.2000	−42.6878	61.5275	74.8858	2.1773
1800	2200	1074	0.2667	−67.3900	39.8186	78.2747	2.6079
1900	2300	1019	0.3333	−44.8424	−10.4151	46.0360	−2.9134
2000	0000	1392	0.4000	−37.4100	7.7818	38.2108	2.9365
2100	0100	1211	0.4667	−12.8173	−13.9109	18.9155	−2.3153

Source: ASPM
f represents the frequency, H_{re} stands for real number, H_{im} for imaginary number.

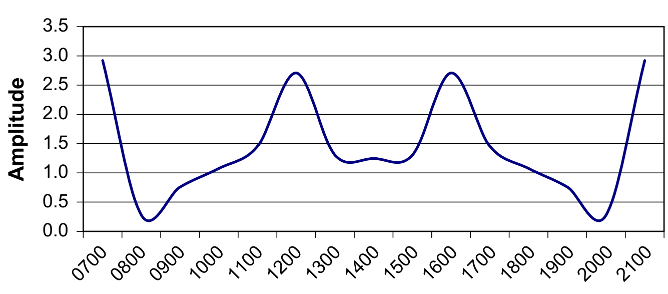

Fig. 1. ATL: Propagation ratio by local hour (summer 2008).

Table 4
Kruskal-Wallis test summer 2000/2007/2008 ($\alpha = 0.05$).

Airport	H	d.f.	p-value	H0: same mean ranks
ATL	22.053	2	0.0000	Reject
BOS	19.975	2	0.0002	Reject
DCA	33.367	2	0.0000	Reject
IND	4.351	2	0.1136	Accept
JFK	19.062	2	0.0001	Reject
LGA	19.419	2	0.0001	Reject
MCO	10.664	2	0.0048	Reject
ORD	2.974	2	0.2261	Accept
PDX	12.232	2	0.0022	Reject
SAN	6.034	2	0.0489	Reject

Source: ASPM.

Table 5
Kruskal-Wallis test (Sampled Airports, by Summer).

Airport	H	d.f.	p-value	H0: same mean ranks
Kruskal-Wallis test, summer 2000 ($\alpha = 0.05$)				
All	44.514	9	0.0000	Reject
Kruskal-Wallis test, summer 2007 ($\alpha = 0.05$)				
All	36.257	9	0.0000	Reject
Kruskal-Wallis test, summer 2008 ($\alpha = 0.05$)				
All	35.361	9	0.0001	Reject

Source: ASPM.

to derive the hourly 'incoming' and 'outgoing' amplitudes. Table 4 shows whether each sampled airport had the same mean ranks or not, by selected time period.

At a 95% confidence level, we reject the null hypothesis that all the sampled airports but IND and ORD had the same mean ranks, when comparing summer 2007 and 2008 with 2000. There was no consistent pattern among the airports, whether they were concentrated markets or not, based on a three-summer comparison.

In the next test, we assume that all the sampled airports have the same mean ranks for a specific summer. However, Table 5 shows that all the airports had different mean ranks for summer 2000, 2007, and 2008.

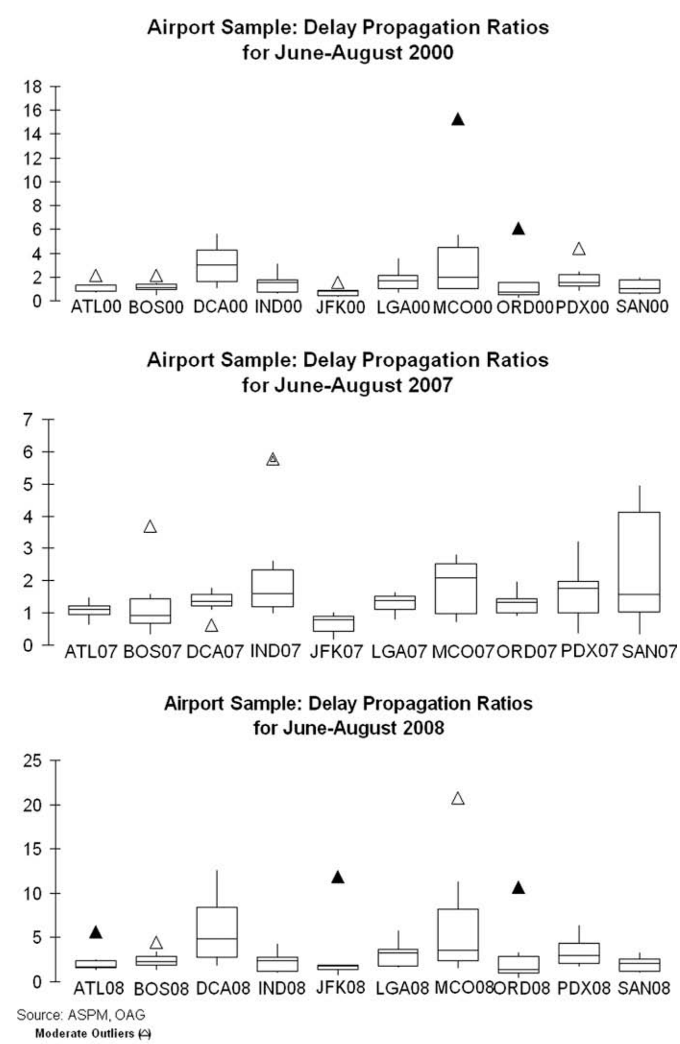

Fig. 2. The boxplots of selected airports.

Table 6
Wilcoxon-Mann–Whitney test (expected value: 232.50/standard deviation: 24.11).

Airport	Summer 2007/2000			Summer 2008/2000			Summer 2008/2007		
	z	*p*-value	H0: same sum of ranks	*z*	*p*-value	H0: same sum of ranks	*z*	*p*-value	H0: same sum of ranks
ATL	−0.58	0.5414	Accept	−3.57	0.0004	Reject	−4.48	0.0000	Reject
BOS	0.50	0.6187	Accept	−3.82	0.0001	Reject	−3.24	0.0012	Reject
DCA	2.78	0.0055	Reject	−2.24	0.0251	Reject	−4.65	0.0000	Reject
IND	−1.49	0.1354	Accept	−1.91	0.0564	Accept	−0.66	0.5069	Accept
JFK	0.21	0.8357	Accept	−3.57	0.0040	Reject	−3.90	0.0001	Reject
LGA	1.37	0.1711	Accept	−2.57	0.0101	Reject	−4.48	0.0000	Accept
MCO	1.24	0.2134	Accept	−1.74	0.0815	Accept	−3.32	0.0009	Accept
ORD	−1.16	0.2455	Accept	−1.41	0.1585	Accept	−1.00	0.3195	Reject
PDX	0.29	0.7716	Accept	−2.99	0.0028	Reject	−2.99	0.0028	Accept
SAN	−1.41	0.1585	Accept	−2.74	0.0062	Reject	0.12	0.9010	Reject

Source: ASPM.

The boxplots illustrate the differences in the delay propagation ratios, by sampled airport and by time period. The boxplots provide information about the medians, first and third quartiles and interquartile ranges. The whiskers extend up to 1.5 interquartile ranges from the first and third quartile. Moderate outliers are those closer than three times the interquartile range and extreme outliers are those further than three times the interquartile range (Fig. 2).

The boxplots in summer 2008 show a compression of the interquartile range for most of the airports except for DCA and MCO. In summer 2008, ATL, JFK and ORD feature extreme outliers, mainly due to poor weather in July at ATL and in June at DCA and ORD. In summer 2007, SAN exhibited the highest interquartile range. There were no extreme outliers in summer 2007 compared with summer 2000 and 2008. In summer 2000, the outliers can be explained by an unusually high percentage of operations in instrument approach conditions in the Northeast part of the United States and at airports such as ORD.

Next, the Wilcoxon-Mann–Whitney test enables to assess whether the delay propagation ratios come from the same distribution. The samples are assumed to be independent and the observations need to be at least ordinal. The Wilcoxon-Mann–Whitney test is useful to determine which populations are different after the Kruskal-Wallis test has rejected H0. Since there are three groups, there are $3(3-1)/2 = 3$ pairs of populations to compare.

If the probability that a delay propagation ratio from one population exceeds another ratio from the second population and that it is greater than 0.50, we accept the null hypothesis that the sum of ranks is identical. In Table 6, only DCA did not have the same sum of ranks when comparing summer 2007 with summer 2000. In a summer 2008/2000 comparison, all but IND, MCO and ORD had different sums of ranks. In contrasting summer 2008 with summer 2007, IND, LGA, MCO and PDX featured the same sums of ranks. As a result, it appears that the status of an airport

Table 7
Summer 2000 correlation coefficients.

	Correlation between vectors of values									
	ATL00	BOS00	DCA00	IND00	JFK00	LGA00	MCO00	ORD00	PDX00	SAN00
ATL00	0.000	−0.475	0.843	0.423	−0.018	−0.524	−0.267	−0.407	−0.320	−0.027
BOS00	−0.475	0.000	−0.436	−0.872	−0.417	0.157	0.544	0.878	0.158	−0.426
DCA00	0.843	−0.436	0.000	0.594	−0.004	−0.518	0.172	−0.169	−0.374	−0.056
IND00	0.423	−0.872	0.594	0.000	0.471	−0.069	−0.102	−0.595	−0.117	0.332
JFK00	−0.018	−0.417	−0.004	0.471	0.000	0.066	−0.239	−0.501	−0.333	−0.390
LGA00	−0.524	0.157	−0.518	−0.069	0.066	0.000	0.000	0.040	0.892	0.450
MCO00	−0.267	0.544	0.172	−0.102	−0.239	0.000	0.000	0.849	−0.009	−0.249
ORD00	−0.407	0.878	−0.169	−0.595	−0.501	0.040	0.849	0.000	0.100	−0.298
PDX00	−0.320	0.158	−0.374	−0.117	−0.333	0.892	−0.009	0.100	0.000	0.689
SAN00	−0.027	−0.426	−0.056	0.332	−0.390	0.450	−0.249	−0.298	0.689	0.000

This is a similarity matrix.

Table 8
Summer 2007 correlation coefficients.

	Correlation between vectors of values									
	ATL07	BOS07	DCA07	IND07	JFK07	LGA07	MCO07	ORD07	PDX07	SAN07
ATL07	0.000	0.038	−0.159	−0.158	0.139	0.525	−0.409	0.026	0.140	0.549
BOS07	0.038	0.000	0.664	−0.128	−0.397	0.373	0.491	−0.345	0.372	−0.309
DCA07	−0.159	0.664	0.000	−0.059	−0.588	−0.318	0.735	−0.349	0.549	−0.712
IND07	−0.158	−0.128	−0.059	0.000	−0.663	0.109	0.038	−0.424	0.708	0.040
JFK07	0.139	−0.397	−0.588	−0.663	0.000	0.158	−0.710	0.755	−0.829	0.526
LGA07	0.525	0.373	−0.318	0.109	0.158	0.000	−0.514	0.122	0.127	0.688
MCO07	−0.409	0.491	0.735	0.038	−0.710	−0.514	0.000	−0.580	0.294	−0.854
ORD07	0.026	−0.345	−0.349	−0.424	0.755	0.122	−0.580	0.000	−0.535	0.388
PDX07	0.140	0.372	0.549	0.708	−0.829	0.127	0.294	−0.535	0.000	−0.209
SAN07	0.549	−0.309	−0.712	0.040	0.526	0.688	−0.854	0.388	−0.209	0.000

This is a similarity matrix.

Table 9
Summer 2008 correlation coefficients.

	Correlation between vectors of values									
	ATL08	BOS08	DCA08	IND08	JFK08	LGA08	MCO08	ORD08	PDX08	SAN08
ATL08	0.000	0.598	0.641	0.540	−0.175	−0.460	−0.253	−0.351	0.065	−0.369
BOS08	0.558	0.000	0.071	−0.164	−0.087	−0.375	0.140	0.366	−0.350	−0.322
DCA08	0.641	0.071	0.000	0.015	−0.162	−0.388	0.254	0.250	0.236	−0.110
IND08	0.540	−0.164	0.915	0.000	0.087	−0.338	0.037	−0.687	0.176	−0.251
JFK08	−0.175	−0.087	−0.162	0.067	0.000	0.320	−0.112	−0.322	−0.340	−0.472
LGA08	−0.460	−0.375	0.388	−0.388	0.320	0.000	0.057	−0.164	−0.613	−0.602
MCO08	−0.253	0.140	0.254	0.037	−0.112	0.057	0.000	0.753	0.054	0.49
ORD08	−0.351	0.366	−0.290	−0.567	−0.322	0.164	0.753	0.000	0.011	0.501
PDX08	0.065	0.250	0.236	−0.176	−0.340	0.613	0.054	0.011	0.000	0.771
SAN08	−0.359	−0.322	−0.118	−0.251	−0.472	0.602	0.349	0.601	0.771	0.000

This is a similarity matrix.

as a concentrated market does not appear to make a difference among the sampled airports in terms of delay propagation when comparing two summers. In the next section, we assess how close each airport is to one another in terms of the delay propagation ratios.

4.2. Proximity analysis

Tables 7–9 feature the SPSS-generated Pearson's correlation coefficients that measure the proximity of airports based on delay propagation ratios for each time period under consideration. The hierarchical cluster analysis provides the dendogram, a visual

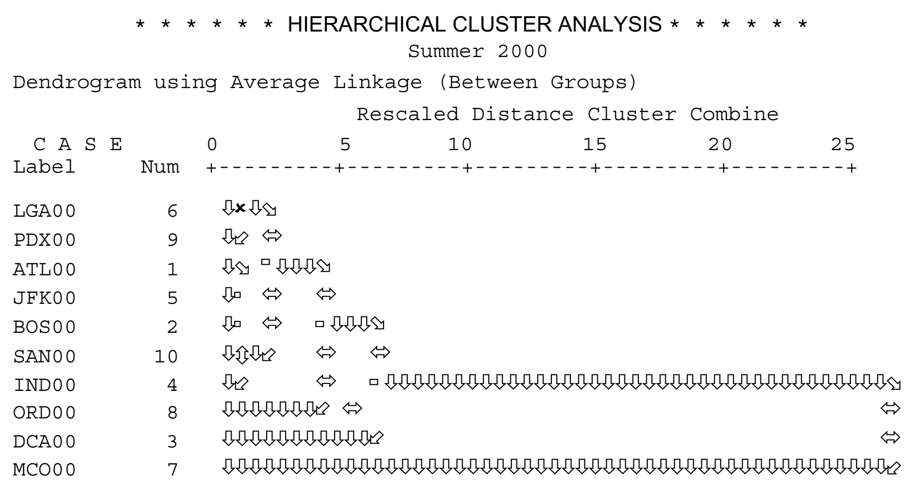

Illustration 1. Hierarchical cluster analysis (summer 2000).

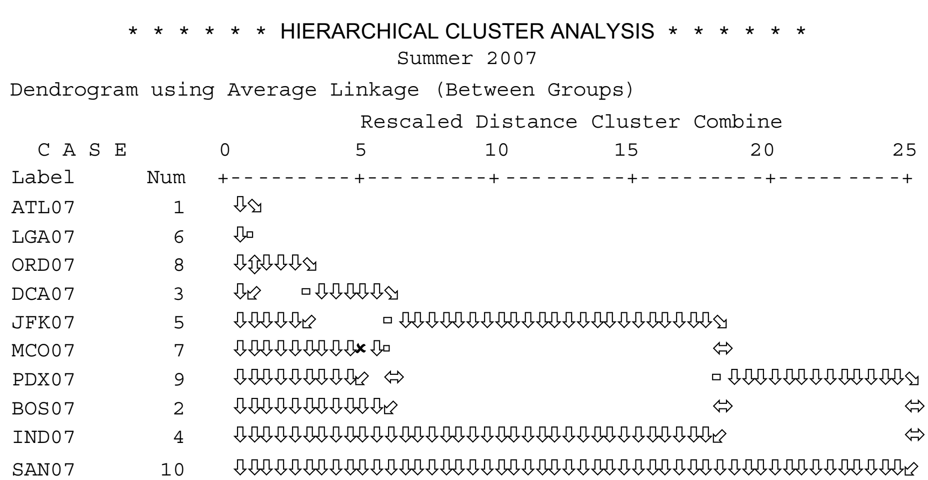

Illustration 2. Hierarchical cluster analysis (summer 2007).

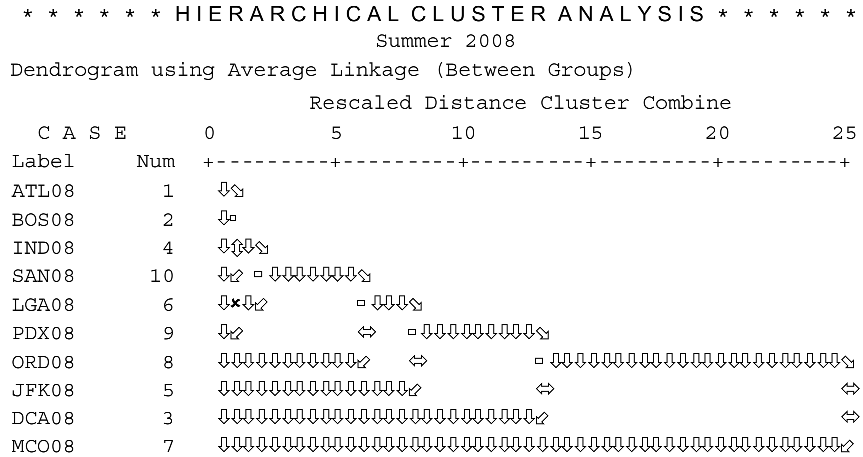

Illustration 3. Hierarchical cluster analysis (summer 2008).

measurement of the distance between each airport and how they cluster together.

There is a strong positive correlation between DCA and ATL, BOS and ORD, PDX and LGA, MCO and ORD. On the other hand, there is a strong negative correlation between BOS and IND. The dendogram shows how each sampled airport is related to one another in term of proximity. Hierarchical cluster analysis enables to group the ten airports into clusters so that similarities may be identified. The dendogram suggests the existence of four major groups in summer 2000.

In Table 8, MCO and DCA, ORD and JFK, and LGA and SAN had the strongest positive correlation among the sampled airports. Illustration 2 does not allow the identification of 'clear-cut' groups among the ten sampled airports. This implies that it is difficult to identify patterns of similarities.

In Table 9, JFK is weakly and negatively correlated to the other airports in the sample. DCA and IND share the highest degree of proximity in summer 2007, followed by MCO and ORD, and LGA and ATL. Illustrations 1 and 3 show that MCO is further away from the other selected airports in summer 2000 and 2008.

In Table 9, LGA and ATL, followed by ORD and JFK, had the highest degree of proximity as measured by Pearson's correlation coefficients. ATL, which has the highest HHI, had the lowest correlations with BOS and SAN, both characterized by a moderate degree of market concentration.

5. Final remarks

Delay propagation is an important issue at a time when the Federal government is attempting to mitigate the impact of congestion at major hubs. It is also of interest to airlines trying to estimate the profitability of existing service and the impact of delays when designing schedules.

Analysis in the frequency domain provides the opportunity to evaluate the intensity of delay propagation on a common scale through the determination of amplitudes and phases derived from the Discrete Fourier Transform.

The goal of this study was to determine whether the propagation of delay was likely to be different at an airport characterized as a concentrated market. The nonparametric tests showed that there was no difference in pairwise and multi-group comparisons based on the degree of market concentration. Further investigation is necessary to identify the factors likely to impact any variation in the amplitudes of propagated delays.

Appendix 1. List and code of sampled airports

Airport code	Airport name
ATL	Atlanta Hartsfield/Jackson International
BOS	Boston Logan International
DCA	Washington Ronald Reagan National
IND	Indianapolis International
JFK	New York John F. Kennedy International
LGA	New York LaGuardia
MCO	Orlando International
ORD	Chicago O'Hare International
PDX	Portland International
SAN	San Diego International

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