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Can we explain airport performance? A case study of selected New York airports using a stochastic frontier model☆

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A B S T R A C T

This paper uses stochastic frontier models to assess whether technical efficiency at Newark Liberty International, New York John F. Kennedy International, and New York LaGuardia airports improved from June to August 2008 compared with the summers of 2000 and 2007. An airport is efficient if it can handle operations on-time by minimizing overall demand and maximizing available airport capacity. Granger-causality tests determined the factors that may cause changes in key components and indicators of airport performance. Compared with the other airports, JFK experienced the greatest improvement in technical efficiency. The Granger-causality tests stressed the significance of airport operations and en route factors in supporting efficiency.

1. Introduction

Airports are complex organizations whose efficiency depends on the coordination of operations such as taxiing, gate departures and arrivals. Airport efficiency hinges on elements that airport management is more likely to control (i.e., the choice of runway configuration) than others (i.e., weather). The differentiation of technical efficiency from stochastic factors, which both influence the overall airport efficiency, makes stochastic frontier models appropriate in the present case study.

This does several things. First, it evaluates the impact of delay reduction initiatives implemented by the US Department of Transportation (USDOT) at the three largest New York City area airports: Newark Liberty International (EWR), New York John F. Kennedy International (JFK), and New York LaGuardia (LGA) airports. These delay management programs included operations caps, airspace and taxiway redesign, among others. Second, it measures whether technical efficiency improved in the summer of 2008 compared with the summers of 2000 and 2007. The three airports are selected because they have been consistently ranked among the most delayed US airports.[1] Third, it identifies the factors that have caused changes in key operational variables and performance indicator.

2. Background

There has recently been a growing number of studies that have used data envelopment analysis (DEA) and stochastic frontier models (SFM) to benchmark airport efficiency.[2] Gillen and Lall (1997), for example, used DEA to assess performance indices in the areas of terminals and airside operations and used these in a Tobit model in which environmental, structural and managerial variables were included. The results provided a 'net' performance index and identified which variables the managers had some control over. Diana (2006) replicated Gillen and Lall's study based on a sample including the Operational Evolution Partnership (OEP 35) airports. DEA was used to benchmark the airports using the percent of on-time gate arrivals as the efficiency criterion and regression analysis to assess the impact of selected input variables on the likelihood that an airport was efficient. The study indicated that 'airport efficiency' for the largest 35 airports in terms of operations had declined after 2004 as airport delays and congestion returned to the 2000 levels.

☆ This paper does not reflect the opinion of the Federal Aviation Administration or that of the Office of Aviation Policy and Plans.

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[1] Among the 35 Operational Evolution Partnership Airports (OEP 35), JFK, LGA and EWR were ranked first, second and third in summer 2007 as the most impacted airports in terms of percent of on-time arrivals. In the summer of 2008, LGA, EWR and JFK were the most delayed airports based on on-time gate arrivals (US Bureau of Transportation Statistics: http://www.bts.gov). The OEP 35 airports represent large commercial airports that account for at least 70% of all the US passengers and were compiled in 2000 based on lists from US Federal Aviation Administration and the US Congress.

[2] According to Forsyth (2000), "Airports have been a surprising late area for application of such techniques as total factor productivity, data envelopment analysis, and costs or production frontier, which have been common in other transportation and utility industries for some years." This may be explained because airports do not provide final but intermediate services to airlines and because airports supply a diversity of services making it difficult to define a common measure of productivity.

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Table 1
Comparison of summer 2000, 2007 and 2008: June–August, all days, 07:00 to 21:59 local time.

	NY Airports			EWR			JFK			LGA		
	2000	2007	2008	2000	2007	2008	2000	2007	2008	2000	2007	2008
Mean SAER	90.980	91.280	90.280	89.260	91.530	91.220	93.010	91.639	90.530	90.680	90.378	89.095
Sigma Squared v	2.343	2.403	3.278	4.415	2.416	2.210	0.398	1.964	3.001	4.009	3.447	3.863
Sigma Squared u	12.072	10.654	10.162	9.050	8.967	9.873	11.164	9.640	9.862	9.973	8.650	9.665
Lambda	5.151	4.434	3.100	2.050	3.710	4.457	28.046	4.091	3.286	2.480	2.509	2.502
Sigma	12.300	10.921	10.677	10.070	9.287	10.119	11.171	9.838	10.308	10.748	9.311	10.408
Sigma Squared	14.415	13.057	13.440	13.465	11.383	12.083	11.562	11.604	12.863	8.190	12.097	13.527
Var[u|e]	0.837	0.816	0.756	0.672	0.788	0.817	0.966	0.831	0.767	1.218	0.715	0.714
Var[u]	4.346	3.835	3.658	3.258	3.228	3.554	4.019	3.471	3.550	3.590	3.114	3.479
Sigma[u]	14.151	12.737	12.791	12.102	10.991	11.790	11.554	11.272	12.305	7.596	11.237	12.561
Sigma[u]/Sigma Squared	0.982	0.975	0.952	0.899	0.966	0.976	0.999	0.971	0.957	0.927	0.929	0.929

Source: ASPM (SAS).
Optimization: Newton-Raphson
Model Type: Production Frontier (Half Normal)

Rendeiro Martín-Cejas (2002) analyzed the productive efficiency of the airport industry. The analysis was carried out using a dual cost function. A translog joint cost function was used to study the productive efficiency of the Spanish airport network. He found some evidence of possible inefficiencies related to the airport's size. This aspect had some significant repercussions in the investment programs (airport planning) and its cost structure.

Pestana Barros (2008a) used a stochastic frontier model to estimate the relative technical efficiency of UK airports from 2000 to 2005 and Pestana Barros (2008b) of Portuguese airports between 1990 and 2000 with a stochastic cost frontier method. In the latter, the rate of technical progress was divided into pure non-neutral and scale-augmenting technical progress. A relatively large amount of waste was found even though technical change contributed to a reduction in costs. Pestana Barros and Dieke (2008) used the two-stage procedure of Simar and Wilson (2007) to estimate the efficiency of Italian airports. First, the airports' relative technical efficiency was estimated using DEA and then the Simar and Wilson procedure was applied to find the most efficient airports in terms of total productivity from 2001 to 2003.

3. Methodology

3.1. The data

Our four data sets (one for each and one for the three airports together) are based on hourly observations from June 1 to August 31, 2000, 2007 and 2008. The period of interest is from 7:00 to 21:59 because it captures the core hours of airport operations.

The stochastic frontier model estimates how arrivals and departures, taxi, airborne, block and gate arrival delays affected changes in the system airport efficiency rates (SAER), while considering the share due to technical inefficiency and stochastic factors. The VAR model helps assess whether some selected operational factors Granger-caused changes in some selected variables. The variables that are part of the models are[3]:

- The SAER measures the contribution of an airport to the efficient operation of the national airspace system (NAS). It is the demand-weighted average of the arrival and departure efficiency rates published daily in the Aviation Systems Performance Metrics (ASPM). The arrival efficiency rate is found by dividing actual arrivals by the lesser of the arrival demand or the airport arrival rate (AAR) provided by US Federal Aviation Administration. It is a measure designed to determine how well the demand for arrivals is met and is determined by three factors:
  - ○ Actual arrivals during a given quarter hour (how many aircraft landed during that quarter hour),
  - ○ Arrival demand for a given quarter hour (how many aircraft wanted to land during that quarter hour),
  - ○ Airport arrival rate (the facility-set airport arrival rate for that quarter hour).

Arrival and departure demand are both designated DEMAND. The computation of the departure efficiency rate is the same as on the arrival side. Therefore, the SAER is computed as:

$$(\text{Departure demand}/\text{overall demand}) \times \text{departure efficiency rates} \\ + (\text{arrival demand}/\text{overall demand}) \times (\text{arrival efficiency rates})$$

- Airport operations (OPS) include air carriers, air taxi, general aviation, and military arrivals and departures.
- Taxi-out delays (DLTOA) represent the difference between the actual and the unimpeded taxi-out times. Unimpeded times are computed for ASQP-reporting carriers and by season. Unimpeded taxi times measure the times from gate-out to wheels-off when there is only one plane ahead in the departure queue.
- Block delays (DLBLOCKA) measure the difference between the actual and the scheduled gate-out to gate-in times.
- Airborne delays (DLAIRA) capture the difference between the actual airborne time minus a carrier's submitted estimated time en route.
- Average minutes of taxi-in delays (DLTIA) are computed as actual minus unimpeded taxi-in times. Taxi-in delays may occur, for example, when a gate is not available for an arriving aircraft.
- The average minutes of delay for all arrivals (DLSCHARRA) represent all the flights arriving one minute or more past their scheduled arrival time.
- Airport departure delays (DLSCHEDAPTA) refer to the difference between the actual and the scheduled time from gate-out to wheels-off.
- The arrival and departure rates (CAPUTIL) called by a facility represent a significant element in the management of airport congestion and reflect:
  - ○ *Weather conditions*. Acceptance rates decline as weather conditions worsen.

[3] The data used comes from a diversity of sources including; ASPM, ARINC, ASQP, the Official Airline Guide (OAG), the US Bureau of Transportation Statistics (BTS), ETMS, and ETMS.

Table 2
New York area airports: stochastic frontier estimates.

Variable name	Variable	Summer 2000			Summer 2007			Summer 2008		
		EWR	JFK	LGA	EWR	JFK	LGA	EWR	JFK	LGA
		Estimate	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate	Estimate
Intercept		94.784*	101.403*	89.498*	93.243*	94.710*	93.559*	91.049*	93.130*	94.327*
Airport operations	ops	0.203*	0.015*	0.293*	0.195*	0.128*	0.200*	0.215*	0.169*	0.219*
Taxi-out delays	dltoa	−0.307*	−0.107*	−0.271*	−0.134*	−0.048*	−0.253*	−0.140*	−0.149*	−0.232*
Block delays	dlblocka	0.437*	0.004	−0.199*	−0.110*	−0.169*	−0.247*	−0.070***	−0.300*	0.049
Airborne delays	dlairaa	−1.061*	−0.209*	−0.128**	−0.434*	−0.230*	−0.157*	−0.391*	−0.294*	−0.489*
Taxi-in delays	dltia	−0.349*	0.119*	0.255*	−0.242*	0.064	0.046	−0.165*	0.083	0.138**
Gate arrival delays	dlscharra	−0.119*	−0.001	−0.084*	−0.054*	−0.026*	−0.070*	−0.041*	0.002	−0.168*
σ_v		4.414*	0.398*	4.008*	2.416*	1.963*	3.446*	2.215*	3.000*	3.862*
σ_u		9.051*	11.163*	9.972*	8.967*	9.640*	8.649*	9.873*	9.861*	9.664*

Source: ASPM.
*, Significant at the 5% level; **, Significant at the 10% level.

- ○ *Runway configurations*. Some configurations are optimal for departures or arrivals given prevailing winds or traffic mix. Moreover, the efficiency of some configurations at a specific airport is interdependent on the runway configuration in use at the other two airports. That is the case of the New York area airports.
- ○ *Scheduled operations*. Arrival and departure rates vary with scheduled traffic.
- Demand for each flight was derived as follows:
- ○ *Start of arrival demand*, namely; wheels-off time + filed en route time (the time when the flight should be at the arrival airport, i.e., wheels-on),
- ○ *End of arrival demand*, namely; wheels-on time (the time when the flight actually arrived at the arrival airport).

On the departure side, it is computed as:

- ○ *Start of departure demand*, namely; gate-out time + unimpeded taxi-out time (the time when the flight should leave the departure airport, i.e., wheels-off),
- ○ *End of departure demand*, namely; wheels-off time (the time when the flight actually left the departure airport).

The hourly data were loaded into SAS to determine the stochastic frontier model estimates and efficiency coefficients. The QLIM procedure is used to derive the stochastic frontier estimates. The VARIMAX procedure provided the VAR estimates, the chi-square and significance values for the Granger causality tests.

3.2. Modeling

Stochastic frontier models (SFM) are parametric in contrast with DEA and assume that deviations from an efficiency frontier may be due to circumstances not entirely under the control of a decision-making unit (DMU) or unit of analysis (i.e., airport). They are used to estimate an efficiency frontier where the output of a DMU is a function of a set of inputs, inefficiency and random errors.

Following Aigner et al. (1977), producer output is the product of the production frontier times technical efficiency (TE) as the ratio of observed outputs to maximum feasible outputs. Here, the SFM indicates the average level of SAER that can be attained from a given level of airport performance characterized by the volume of operation, as well as taxi, block, airborne and gate arrival delays. Technical inefficiency is defined as the shortfall of SAER from its maximal possible level given by the stochastic frontier [$f(x_i;\beta)+v_i$]. The SFM can be expressed as:

$$Y_i = f(x_i;\beta) \times \mathrm{TE} \tag{1}$$

where $\ln y_i = \beta_0 + \sum_n \beta_n \ln x_i + v_i - u_i$ and $\mathrm{TE}_i = \exp\{-u_i\}$ with $u_i \geq 0$.

v_i is the noise component with a two-sided normal distribution and accounts for measurement errors while u_i is the non-negative technical inefficiency parameter with a half normal distribution.[4] In Eq. (1), $v_i - u_i$ represents the compounded error ε_i. For estimation the SFM is characterized as:

$$\begin{aligned}\ln \mathrm{SAER} = {} & \beta_0 + \beta_1 \times \ln \mathrm{OPS} + \beta_2 \times \ln \mathrm{DLTOA} + \beta_3 \\ & \times \ln \mathrm{DLBLOCKA} + \beta_4 \times \ln \mathrm{DLAIRA} + \beta_5 \\ & \times \ln \mathrm{DLTIA} + \beta_6 \times \ln \mathrm{DLSCHARRA} + \mathrm{v}_i - u_i\end{aligned} \tag{2}$$

The other key components in SFM seen in Table 1 are λ (lambda) = σ_u/σ_v (the contribution of u and v to the compounded error) and σ (sigma) = $(\sigma_u^2/\sigma_v^2)^{1/2}$ (the variance parameter in the compounded distribution). If $\lambda = 0$, then every DMU would operate on the efficiency frontier.

VAR models are useful in examining dynamic relationships among several variables and in testing the hypothesis that one or more variables not 'Granger cause' the others.[5] In the reduced form of the first-order VAR model, each variable is a linear function of its own past values, the past values of all other variables considered, and a serially uncorrelated error term. The VAR(p) model is characterized as:

$$y_t = c + A_1 y_{t-1} + A_2 y_{t-2} + A_p y_{t-p} + \varepsilon_t \tag{3}$$

where c is a $k \times 1$ vector of constants, A_n is a $k \times k$ matrix (for every $i = 1, \ldots, p$) and ε_t is a $k \times 1$ vector of error terms.[6]

4. Results

Table 1 gives the estimates for the stochastic frontier models involving each airport individually and as a whole.

The table shows that only EWR exhibited a higher mean SAER in the summer of 2008 than in 2000 when adverse weather conditions on the East Coast and the Mid-West affected the performance

[4] The technical inefficiency parameter can also have a different distribution: truncated normal, exponential (with mean λ), or gamma (with mean λ and degree of freedom m).

[5] According to Greene (2008), "Causality in the sense defined by Granger (1969) and Sims (1972) is inferred when lagged values of a variable, say, x_t, have explanatory power in a regression of a variable y_t on lagged values of y_t and x_t."

[6] The model assumes that the mean of the error is zero, no serial correlations among error terms and the covariance matrix of error terms is positive definite. Sims (1980) provided an explanation of the use of VAR models and their characteristics.

Table 3
New York area airports: Granger causality Wald test estimates.

	EWR			JFK			LGA		
	Chi-square	Pr > ChiSq	Null hypothesis	Chi-square	Pr > ChiSq	Null hypothesis	Chi-square	Pr > ChiSq	Null hypothesis
June–August 2000 ($\alpha = 0.05$)									
Test 1	29.92	0.000*	Reject	155.76	0.000*	Reject	16.27	0.000*	Reject
Test 2	86.92	0.000*	Reject	40.73	0.000*	Reject	14.48	0.002*	Reject
Test 3	29.77	0.000*	Reject	42.89	0.000*	Reject	46.93	0.000*	Reject
June–August 2007 ($\alpha = 0.05$)									
Test 1	63.13	<0.0001	Reject	154.64	0.000*	Reject	12.88	0.001*	Reject
Test 2	385.27	<0.0001	Reject	64.34	0.000*	Reject	2.35	0.503***	Accept
Test 3	84.24	<0.0001	Reject	16.33	0.002*	Reject	15.93	0.003*	Reject
June–August 2008 ($\alpha = 0.05$)									
Test 1	48.22	<0.0001	Reject	146.52	0.000*	Reject	11.92	0.002*	Reject
Test 2	48.15	<0.0001	Reject	58.09	0.000*	Reject	22.91	0.000*	Reject
Test 3	55.84	<0.0001	Reject	16.03	0.003*	Reject	31.77	0.000*	Reject

Source: ASPM.
Notes: Test 1, the percent capacity utilized is influenced by itself and not by airport departure delays and overall demand. Test 2, demand is influenced by itself and not by block delays, taxi-in and taxi-out delays. Test 3, the SAER is influenced by itself and not by airport departure delays, block delays, taxi-in and taxi-out delays.
*, Significant at the 5% level; **, significant at the 10% level.

of the NAS. The increase in lambda at EWR suggests that technical inefficiency based on the model increased in 2008 compared with the summers of 2000 and 2007.

Also, variations in the compounded error terms are more linked to technical inefficiency than random errors. This contrasts with JFK and LGA. There may be several reasons fro this. First, as airlines anticipate en route and terminal delays, they tend to add additional time into their schedules ('schedule padding'). Secondly, over-scheduling at peak times exacerbates the problems of congestion, especially in poor weather conditions. Third, air traffic control usually resorted to ground delay programs (i.e. traffic management initiatives or TMIs) to manage expected surges in delays and congestion. At the three combined airports, there were 11,742 delays due to volume[7] in summer 2008 compared with 2,620 and 7,561 respectively in summer 2000 and 2007.

Table 1 indicates that JFK experienced the greatest increase in efficiency among the New York airports as measured by changes in the lambda parameter. Compared with the other airports, the lambda for LGA remained relatively stable. This may be because, first, the number of operations at LGA is capped and second, the arrival and departure flows depend on how the terminal radar approach control (TRACON) allocates traffic among the NY area airports. The choice of configuration at JFK impacts efficiency at LGA and even EWR through potential approach maneuvering and longer taxi times. Finally, the proportion of regional jets flying in and out of LGA in the summer 2008 was higher (38.2%) than at EWR (29.5%) and at JFK (27.2%). Regional jets fly slower than larger jets but at the same altitude, which impacts separation and therefore runway occupancy.

Another way of measuring the progress made by each airport toward efficiency is to consider the variance of the asymmetric component u_i. The greater the variance in u_i, the more significant the inefficiency of some observations relative to others. As the error variance goes toward zero, so does inefficiency. At the three airports, the variance of u_i increased in summer 2008 compared with summer 2007. It was lower in summer 2008 compared with summer 2000 except at EWR and for the New York area airports as a whole.

Table 2 provides SFM estimates. In the case of EWR, OPS emerges as the most significant factor impacting on the efficiency frontier. The magnitude of airborne delays has significantly changed at EWR in between the summer of 2000, 2007 and 2008. The use of ground delay programs may have increased demand and airborne delays.

The results suggest that OPS, DLTIA and DLSCHARRA impacted the efficiency level of JFK. Variations in the compounded error term could be attributed to technical inefficiency in 2008 compared with the summer of 2007. Although the share of stochastic factors in the compounded error term increased in 2008, it was higher 2000 when poor weather conditions introduced many uncertainties in the operations of the NAS.

The significance and magnitude of OPS in the periods may be explained by caps on the number of operations ("slot controls"). On March 30, 2008, the FAA issued an order (to expire on October 24, 2009) that limited the number of hourly operations between 06:00 and 21:59 at JFK to 81. At EWR, the caps, that apply both to domestic and international carriers, allowed an average of 83 flights per hour during peak periods. Besides the limitation of scheduled operations at the airports, there is also the on-going redesign of the New York airspace and the implementation of the airspace flow-control program in 2006.

The on-going redesign of the New York airspace may explain why the decline in the airborne delays has contributed to improvements in technical efficiency at the airports. According to ASPM, the average minutes of airborne delays declined from 5.36 in the summer of 2007 to 4.89 in 2008 at EWR and from 6.66 to 5.93 min at JFK. Delays did not change at LGA. The redesign airspace consists of four phases, each of which takes about 18 months to implement. The first two stages pertain to procedural changes and the integration of TRACON and New York Center. The last two affect boundary changes and transfer of sectors. In December 2007, EWR implemented fanned headings from runway 22L|22R, which eliminates the need for departing aircraft to follow each other out one-by-one. Other changes include dispersal headings and RNAV procedures off LGA's runway 31 and 4. At JFK, changes involve 31R right turn departure procedures. The Air Traffic Control System Command Center (ATCSCC) initiated an airspace-specific procedure called Airspace Flow Control Program[8] (AFP) to

[7] According to OPSNET Order JO 7210.55E, "[Volume] delays must only be reported as volume when the airport is in its optimum configuration and no impacting conditions have been reported when the delays were incurred."

[8] See Federal Aviation Administration Advisory Circular, Airspace Flow Program, AC 90-102, May 1, 2006. When an AFP is issued, the FAA will send an Advisory that is accessible at http://www.fly.faa.gov/adv/advAdvisoryForm.jsp.

alleviate the effects of thunderstorms and poor weather on en route navigation. AFP's control flights through a specific section of airspace rather than flights heading to a particular airport (usually through ground delay programs). AFPs provide pilots with choices, such as rerouting around thunderstorm areas, which is not possible under a GDP.

The three Granger causality tests we use are:

- *Test 1.* H0: the percent capacity utilized is influenced by itself and not by airport departure delays and airport demand.
- *Test 2*. H0: demand is influenced by itself and not by block delays, taxi-in and taxi-out delays.
- *Test 3*. H0: the SAER is influenced by itself and not by airport departure delays, block delays, taxi-in and taxi-out delays.

Table 3 report the Granger Causality Wald test estimates generated by the VARMAX procedure in SAS.

At a 95% confidence level, we accept the alternative hypothesis that the percent capacity utilized at the three airports was Granger-caused by airport departure delays and overall demand in the summers of 2000, 2007 and 2008. We are 95% confident that overall demand was influenced by block delays, taxi-in and taxi-out delays at the three airports except at LGA in the summer of 2008. In 2000, 2007 and 2008, the SAER was Granger-caused by airport departure delays, block delays, taxi-in and taxi-out delays at the airports. These tests confirm that the improvement of airport efficiency did not depend only on airport operational factors, but also on the en route environment that influenced block and airborne delays.

5. Final comments

The stochastic frontier model captures gains in efficiency in the summer of 2008 at JFK and LGA compared with the other periods in the study. EWR was the exception and it continued to be impacted by poor on-time performance. The study also suggests that JFK's capping of operations at peak times may have had a greater impact on technical efficiency compared with EWR where traffic flows were more likely affected by traffic management initiatives.

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