# Ownership Forms Matter for Airport Efficiency: A Stochastic Frontier Investigation of Worldwide Airports

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**Abstract**

We study the effects of ownership forms on airports' cost efficiency by applying stochastic frontier analysis to a panel data of the world's major airports. Our key findings are: (a) Countries considering privatization of airports should transfer majority shares to the private sector; (b) Mixed ownership of airport with a government majority should be avoided in favor of even 100% government owned public firm; (c) U.S. airports operated by port authorities should consider to transfer ownership/management to independent airport authorities; and (d) Privatization of one or more airports in cities with multiple airports would improve the efficiency of all airports.

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**By Tae H. Oum, Jia Yan, and Chunyan Yu**

## 1. Introduction

An airport links local industries and residents to new markets, products, customers, relatives and friends around the world, making it a critical component of a region's trade and commerce with other regions and countries[1]. An efficient airport provides important economic catalysts that enable the local and regional economy to thrive and improve the quality of life in the region. Governments around the world have taken measures to privatize and/or commercialize airports for various purposes including for access to private sector financing for capacity expansion and improvement of economic efficiency and productivity of airport operations. Although different ownership forms and institutional arrangements (henceforth referred to as "ownership forms") have been adopted in different countries over the last two decades, there has been a lack of rigorous econometric evidence for the effects of various ownership forms on improving airport efficiency. This paper attempts to help fill this gap in the literature by developing an advanced form of stochastic frontier model to investigate how different ownership forms affect airport efficiency by applying it to an extensive panel data of worldwide airports.

Major airports around the world were traditionally owned and operated by national or local governments. However, starting with the privatization of the three airports in London (Heathrow, Gatwick, and Stansted) and four other major airports in the UK to British Airport Authority (BAA plc) in 1987, the role of the governments in airport ownership and management has been changing significantly over time. Many countries have introduced various forms of private sector involvement to

[1] Bruckner (2003) provides some empirical evidence on the link between airline traffic and employment in US metropolitan areas.

the ownership/management of airports. For example, Rome's Leonardo Da Vinci Airport is now fully privatized, and the majority stakes of Copenhagen Kastrup International Airport, Vienna International Airport, and Brussels International Airport have been sold to private and institutional shareholders. All major Australian airports have been privatized while majority stakes of Wellington International Airports in New Zealand have been privatized. In Asia, Mumbai and New Delhi airports in India have been privatized, whereas minority stakes of Beijing Capital International Airport, Shanghai Pudong Airport, Malaysia Airports Holdings Bhd, etc have been sold to private investors. Tokyo's Narita International Airport was corporatized in 2003 and is expected to be privatized in the near future. Many airports in other Asian countries, South Africa, Argentina, and Mexico have also been and/or are in the process of being privatized partially or wholly.[2]

In contrast to this worldwide trend of privatization, however, the United States and Canada have not embraced the privatization policy. In Canada, the federal government has retained ownership of its major national airports, but commercialized these airports by transferring their management and operation to "not-for-profit" locally-based airport authorities under long term lease contracts. In the United States, airports have remained mostly municipal or regional government-owned and operated. However, the government ownership and management of the U.S. airports are considered to be rather different from those of other countries in that there is substantial private sector involvement in management decisions concerning key airport activities and capital investment decisions. For example, because some major capacity expansion projects are financed through revenue bonds guaranteed by the major tenant airlines, these airlines have substantial power over airports' decisions on capacity investment, user charges, and other key strategic decisions. Although not strictly following the worldwide privatization trend, many airports in the United States, have in recent years begun to be

[2] See Oum, A. Zhang and Y. Zhang (2004) for the ownership list of 60 major airports in Asia, Europe, North America, and Oceania.

organized as quasi-privatized airport authorities. These airport authorities are similar in nature to that of Canadian airport authorities, insofar as they are not-for-profit/non-shareholder entities that re-invest retained earnings into future airport development programs and are by-and-large financially self-sustaining. The U.S. also has several airports run by local Port Authorities, whereby a Port Authority operates the local seaport(s) as well as the local airport(s).

As stated earlier, the objective of this paper is to examine how various ownership forms affect the efficiency of airport operations. To achieve this objective, we construct and estimate a stochastic cost frontier model with a flexible empirical specification. The stochastic frontier models have been very widely used as a means of measuring the deviation of a firm's (agency's) efficiency as compared to the best achievable target (frontier). Our cost frontier model is specified in a *translog* form and estimated using a Bayesian approach.

Our empirical findings suggest: (a) Countries considering privatization of airports should transfer majority shares to private sector; (b) Mixed ownership of airports with a government majority should be avoided in favor of even 100% government owned public corporation, despite the fact that many countries regard P3 (Public-Private-Partnership) with government majority as a politically acceptable model to raise private funds for infrastructure capacity expansion without losing government control; (c) The U.S. should reconsider ownership and management of airports by port authorities; These ports authorities or responsible governments should consider creating independent airport authorities to which to transfer ownership/management of airport, independently from the port management; and (d) Privatization of one or more airports in cities with multiple airports would improve the efficiency of all airports.

## 2. Literature Review and Issues Surrounding Airport Ownership

The effects of ownership on firms' productive efficiency have been an important research topic. The agency theory and strategic management literature suggest that ownership influences firm performance because different owners pursue different goals and have different incentives. Under government ownership and management, a firm is run by bureaucrats whose objective function is an weighted average of social welfare and their personal agenda. Under private ownership, by contrast, the firm maximizes profit (shareholder value). A common-sense view is that government-owned firms are less efficient than their private sector counterparts operating in similar situations. The main arguments supporting this view are: (1) the objectives given to the managers of government owned firms are vaguely defined, and tend to change as the political situation and relative strengths of different interest groups change (De Alessi, 1983; Levy, 1987); and (2) The high mismatch between management's incentives and the interest of the owner (nation) increases inefficiency as documented extensively in agency theory literature (see, for example, Zeckhauser and Horn, 1989).

However, neither empirical nor theoretical evidence presented in the economics literature is conclusive with respects to relative efficiency of public vs. private firms. De Fraja (1993) questions the logic of the main arguments, and shows, via a principal-agent model, that government ownership "is not only not necessarily less productively efficient, but in some circumstances more productively efficient". Vickers and Yarrow (1991) suggest that private ownership has efficiency advantages in competitive conditions, but not necessarily in the presence of market power. They further suggest that even under competitive market conditions, government ownership is not inherently less efficient than private ownership, and that competition is the key to efficiency rather than ownership per se. Willner and Parker (2007) find that privatization may increase a firm's marginal cost.

Also, the results of empirical studies on this issue are far from conclusive. For example, Bennett and Johnson (1980) and De Alessi (1980) provide strong evidence for the view that private firms would perform better than government owned firms, whereas Boyd (1986) and Millward and Parker (1983) find no systematic evidence that public enterprise are less cost efficient than private firms.

Further complicating the ownership-performance debate is the presence of mixed ownership regimes embodying elements of government and private ownership. Bos (1991) provides an excellent theoretical treatment on the behavior of mixed ownership firms. On one hand, mixed ownership may facilitate the role of the government as a “steward” in private firms that are dominated by a strategic investor or where there is a lack of market discipline. On the other hand, mixed ownership arrangements may blend the worst qualities of government and private ownership. Thus, the resulting effects of mixed ownership on firm performance are not clear from a theoretical perspective. Empirical evidence is limited, and fails to provide any clarification on the issue. Boardman and Vining (1989) find that mixed ownership perform no better and often worse than government owned firms, which may be caused by the conflict between public and private shareholders. This finding is supported by the analytical and empirical productivity growth investigations of Ehrlich et al. (1994).

A number of studies have examined the performance of airports using different methodologies. For example, Hooper and Hensher (1997) examine the performance of six Australian airports over a 4-year period using the total factor productivity (TFP) method. Gillen and Lall (1997) develop two separate data envelopment analysis (DEA) models to evaluate terminal and airside operations separately from each other, and applied them to a pooled data of 21 top U.S. airports for the 1989-93 period. Nyshadham and Rao (2000) evaluate the efficiency of European airports using TFP and examine the relationship between the TFP index and several partial measures of airport performance. Sarkis (2000) evaluate the operational efficiency of U.S. airports and reach the tentative conclusion that major hub airports are more efficient than spoke airports. Adler and Berechman (2001) use DEA to analyze airport quality and performance from the airlines' viewpoint. Martin and Roman (2001) and Martin-Cejas (2002) apply DEA and *translog* cost functions, respectively, to evaluate the performance of Spanish airports. Abbott and Wu (2002) investigate the efficiency and productivity of 12 Australian airports for the period 1990-2000 using a Malmquist TFP index and DEA. Pacheco and Fernandes (2003) examine the efficiency of 35 Brazilian domestic airports and identify the avenues for improvements, and Pels et al (2003) investigate the technical and scale efficiency of European airports, both using the DEA method. Barros and Sampaio (2004) use DEA to evaluate the technical and allocative efficiency of Portuguese airports, and Holvad and Graham (2004) study the efficiency performance of UK airports using DEA. Martin and Roman (2006) compare the Surface Measure of Overall Performance (SMOP) and DEA in measuring the relative performance of Spanish airports. And in a later paper, Martin and Roman (2007) propose to investigate the economic efficiency of Spanish airports through airport typology. Humphreys and Francis (2002) provide a good discussion of the changing nature of the performance measurement of airports in response to changing organizational contexts.

In addition to the efficiency and productivity performance, there have been studies on administrative and strategic aspects of airport ownership and governance structures. For example, Bacot and Christine (2006) conduct a survey of airport managers of primary US airports to examine the administrative setting of airport authorities/airport operators in the US within local governments. Lyon and Francis (2006) explore the challenges facing airports managers in New Zealand where airports are run as commercial entities under a variety of ownership structures. Halpern and Pagliari (2007) investigate the relationship between governance structures and the market orientation of airports with the focus on Europe's peripheral areas.

Despite the diversity of airport ownership and institutional arrangements, the aforementioned studies, with the exception of Parker (1999)[3], have largely ignored the effects of institutional factors on airports' productive efficiency. Airola and Craig (2001) and Craig et al (2005) appear to be the only studies that explicitly examine the effects of U.S. airports' institutional arrangement on efficiency. Based on a sample of 51 US airports, they distinguish two types of airport governance structures: city operated airports versus airport authority operated airports. Their results suggest that the authority-operated U.S. airports out-perform city-operated U.S. airports in terms of technical efficiency. It is noted, however, that their study uses only one output measure (number of aircraft movements) in measuring efficiency. As articulated in Oum, Yu and Fu (2003), the omission of other outputs such as commercial services is likely to bias efficiency results as it underestimates productivity of the airports with proactive managers who focus on exploiting the revenue generation opportunities from non-aviation business. Given that non-aeronautical outputs can account for as much as 70 % of total revenue an airport generates, the productivity measures ignoring the non-aeronautical services (including concession) would be seriously biased against the airports generating a high proportion of their total revenues from commercial services.

Furthermore, an important issue that has not received due attention in the ownership-performance debate for airports is whether the effects of ownership forms on airport efficiency would depend on the competitive condition in which an airport operates. Many airports are considered to possess considerable market power as the only airport serving a region or a metropolitan area[4], whereas some major metropolitan areas are served by multiple airports[5], such as London, Paris, Los Angeles, New York – New Jersey, Washington DC, etc, that may potentially compete against each other. The

[3] Using Total Factor Productivity analysis, Parker (1999) found that BAA privatization had no noticeable impact on airport technical efficiency while Yokomi (2005) using Malmquist TFP index method found that almost all airports under BAA Plc. have improved technical efficiency after privatization.

[4] Note that the market power for these airports applies to the origin-destination traffic only.

[5] In many cases, these airports are owned and operated by the same operator.

extent to which the market structure influences the effects of ownership forms on airport efficiency has important implications for ownership restructuring. What would be the most effective ownership form for improving airport efficiency in the presence of multiple airports? Would a non-profit airport authority be more efficient than a government corporation? The answers to such questions would be critical for policy makers in deciding the forms/formats for airport ownership restructuring. Unfortunately, there does not appear to be any clear consensus among the theoretical arguments in this regard as discussed earlier in this section. Therefore, this issue is more of an empirical question. There are, however, some studies on airline competition and network structure that may have implications for airport efficiency performance. Examples include: Flores-Fillol (2007), Grammig, et al (2005), Daniel and Thomas Harback (2005), Bhadra and Texter (2004), and Cohen and Morrison Paul (2003).

The above discussion leads us to conclude that there is a need for a rigorous econometric study for measuring the effects of ownership and institutional arrangements on the efficiency of airports using a comprehensive cost model which is formulated consistently with micro-economic theory.

## 3. The Econometric Model

The empirical model to quantify the effects of ownership forms on airport efficiency is under the stochastic frontier framework first developed by Aigner et al. (1977) and Meeusen and van den Broeck (1977). The stochastic frontier method postulates that some firms fail to achieve the cost (production) frontier. That is, inefficiencies exist, and these inefficiencies can not be fully explained by measurable variables. Thus, a one-sided error term, in addition to the traditional symmetric noise term, is incorporated in the model to capture inefficiency that can not be explicitly explained.

In the short run, if the airport management tries to minimize production cost $(C)$ given outputs $(Q)$, variable input prices $(W)$, and fixed capital inputs $(K)$, the outcome can be summarized by a short run variable cost function, $C_i^*(Q_{it}, W_{it}, K_{it}, t)$, where $i$ indexes airports and $t$ indexes time. In reality, airports may deviate from the cost minimization objective for various reasons including airport ownership forms, and such deviations indicate the existence of inefficiency. For airport $i$, the deviation of its actual cost from the frontier, $\Delta_i$, is regarded as a random draw from a distribution conditional on its ownership form $(Z_i)$. The density function of the distribution, $f(\Delta_i | Z_i)$, is restricted to the positive range because it measures cost inefficiency. The conditionality of the deviation on ownership forms captures the effects of ownership on cost efficiency, and the random part of the deviation captures the effects of all unobserved factors. By modeling the deviation from the frontier as random, our model is an example of the random effects stochastic frontier model described in Kumbhakar and Lovell (2000).

Formally, the observed actual production cost (after taking log) of airport $i$ at time $t$ is expressed as

$$\ln C_{it} = \ln C_i^*(Q_{it}, W_{it}, K_{it}, t) + \Delta_i + \varepsilon_{it}^c \tag{1}$$

where $\varepsilon_{it}^c$ represents the noises associated with the cost observations. Our model includes three outputs in vector $Q_{it}$ (number of passengers $q_{1it}$; number of aircraft movements $q_{2it}$; and non-aeronautical output $q_{3it}$), two variable input prices in vector $W_{it}$ (labor price $w_{1it}$; and non-labor variable input price $w_{2it}$), and two fixed capital inputs in vector $K_{it}$ (number of runways $k_{1it}$; and terminal size $k_{2it}$).

### 3.1 Specification of the cost frontier

To estimate the empirical model, the log variable cost frontier is approximated by the following *translog* functional form:

$$\ln C_i^*(Q_{it}, W_{it}, K_{it}, t) \approx \ln \tilde{C}_i(Q_{it}, W_{it}, K_{it}, t) = \alpha_{it} + \sum_{j=1}^{3} \beta_j \ln q_{jit} + \sum_{j=1}^{2} \lambda_j \ln k_{jit} + \sum_{j=1}^{2} \delta_j \ln w_{jit}$$
$$+ \frac{1}{2} \sum_{j=1}^{3} \sum_{n=1}^{3} \phi_{jn} \ln q_{jit} \ln q_{nit} + \sum_{j=1}^{3} \sum_{n=1}^{2} \gamma_{jn} \ln q_{jit} \ln w_{nit} + \sum_{j=1}^{3} \sum_{n=1}^{2} \rho_{jn} \ln q_{jit} \ln k_{nit} \qquad (2)$$
$$+ \frac{1}{2} \sum_{j=1}^{2} \sum_{n=1}^{2} \tau_{jn} \ln w_{jit} \ln w_{nit} + \sum_{j=1}^{2} \sum_{n=1}^{2} \zeta_{jn} \ln k_{jit} \ln w_{nit} + \frac{1}{2} \sum_{j=1}^{2} \sum_{n=1}^{2} \psi_{jn} \ln k_{jit} \ln k_{nit}$$

The intercept $\alpha_{it}$ varies across airports in order to capture the difference in cost frontier (individual heterogeneity across airports in adopted technologies) caused by the factors beyond managerial control; and varies over time in order to reflect technical change. Cost frontiers may be different from airport to airport because of differences in operating environments (such as weather conditions), general labor skills, culture factors, etc. which are not included in our model explicitly. Therefore we specify $\alpha_{it}$ as:

$$\alpha_{it} = \bar{\alpha} + [\Pi_i, D_{it}]\Theta + \nu_i, \nu_i \sim N(0, \sigma_\nu^2) \qquad (3)$$

where $\Pi_i$ is the vector of airport $i's$ characteristics; $D_{it}$ is the year dummy variables; the random term $\nu_i$ captures the difference in cost frontiers that can not be explained by factors in $\Pi_i$.

### 3.2 Specification of the random deviation

The random deviation from the frontier is parameterized as:

$$\Delta_i = \exp(Z_i \Gamma_i) \qquad (4a)$$

$$\Gamma_i \sim N(\bar{\Gamma}, \Omega) \qquad (4b)$$

where $\Omega$ is a diagonal matrix; $Z_i$ is the dummy variable vector indicating ownership forms; $Z_i = j$ indicates that the ownership form of airport $i$ is $j$.

With this model specification, the observed cost is $C_{it} = C_i^*(Q_{it}, W_{it}, K_{it}, t)\exp(\Delta_i)$, where $\exp(\Delta_i)$ captures the deviation from the efficiency frontier, and is defined as cost inefficiency. When an airport is on the frontier, $\exp(\Delta_i)$ equals to one. For ease of interpretation and following the common practice, we use the following indicator as the measure of the mean efficiency level of all airports under ownership form *j*

$$h(j) = \frac{1}{\exp\left(E\left(\Delta_i \middle| Z_i = j\right)\right)} \tag{5}$$

This efficiency level can be interpreted as the percentage of achieving the frontier, and is the parameter of our interest for identifying the effects of ownership forms on cost efficiency[6].

### 3.3 Variable input share equation

To improve the efficiency of estimation, it is customary to estimate the stochastic cost frontier equation jointly with input share equations. In order to avoid the singularity problem, we chose to add the labor share equation only[7].

$$\begin{aligned} S_{it}^* &\equiv \frac{\partial \ln C_i^*(Q_{it}, W_{it}, K_{it}, t)}{\partial \ln w_{1it}} \approx \frac{\partial \ln \tilde{C}_i(Q_{it}, W_{it}, K_{it}, t)}{\partial \ln w_{1it}} \\ &= \delta_1 + \sum_{j=1}^{3} \gamma_{j1} \ln q_{jit} + \sum_{j=1}^{2} \tau_{j1} \ln w_{jit} + \sum_{j=1}^{2} \zeta_{j1} \ln k_{jit} \end{aligned} \tag{6}$$

In order to reflect the panel data structure, we add the following noise term into the labor share equation, and the noise term is divided into two components:

$$\mu_{it} = \xi_i + \varepsilon_{it}^s, \text{ with } \xi_i \sim N\left(0, \sigma_\xi^2\right) \tag{7}$$

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[6] As was done in Oum and Yu (1998, 2004), researchers may be also interested in identifying efficiency levels of individual firms (agents), measured by $h_i = \dfrac{1}{\exp(\Delta_i)}$.

[7] Our empirical results are invariant to the choice of either labor cost share equation or other variable input cost share equation.

where $\xi_i$ is the random individual effects of airport *i*. The labor share equation is estimated jointly with the frontier cost function in (2) via the seemingly unrelated regression (SUR) specification.

## 4. Estimation Procedure

The Markov Chain Monte Carlo (MCMC) simulation under the Bayesian framework is used to make inference about the unknown parameters $\Xi$. Examples of Bayesian analysis on stochastic frontier models include Atkinson and Dorfman (2005a, 2005b), Fernandez et al. (1997), Huang (2004), Kleit and Terrell (2001), Koop et al. (1995, 1997), Kumbhakar and Tsionas (2005), Lewis and Anderson (1999), McCauland (2007), O'Donnell and Coelli (2005), and Tsionas (2002). The Bayesian inference can be facilitated by the data augmentation proposed by Tanner and Wong (1987). In particular, rather than working directly on the posterior of $p(\Xi|Data)$, we work on the posterior of $p(\Xi,\{\nu_i,\xi_i,\Gamma_i\}|Data)$ by taking the unobserved individual airport level parameters as missing data to be augmented. $\{\nu_i,\xi_i,\Gamma_i\}$ is used to denote the collection of the individual level parameters for all airports. The data augmented posterior is

$$p(\Xi,\{\nu_i,\xi_{i,}\Gamma_i\}|Data) \propto \rho(\Xi)\cdot\prod_{i=1}^{N}\left\{\phi(\Gamma_i;\overline{\Gamma},\Omega)\cdot\phi(\nu_i;\sigma_\nu^2)\cdot\phi(\xi_i;\sigma_\xi^2)\prod_{t=1}^{T_i}BVN(y_{it},S_{it};\Xi)\right\} \tag{8}$$

where $p(\Xi)$ is the prior of the parameters; $\phi(\cdot)$ represents the univariate normal density function, and $BVN(\cdot,\cdot)$ represents the bivariate normal density function; $T_i$ is the number of observations on airport $i$. Since the functional form of the data augmented posterior is complicated, it is impossible to derive its analytical properties. Therefore, we use the Monte-Carlo simulation to take random draws from the posterior and the empirical properties of the draws will be used to approximate the theoretical ones. The MCMC simulation is a special way to implement Monte-Carlo simulation, and it takes random draws by simulating a Markov process in the space of $(\Xi,\{\nu_i,\xi_{i,}\Gamma_i\})$ that converges to $p(\Xi,\{\nu_i,\xi_i,\Gamma_i\}|Data)$. A good introduction to the MCMC simulation can be found in Gelman *et al.* (2004). Appendix A of this paper outlines the algorithm for implementing the MCMC simulation, and more details of the algorithm can be found in Oum, Yan, and Yu (2007).

The Bayesian estimation approach adopted in this paper has many advantages. First, since the data likelihood without data augmentation involves multiple integrations over the random parameter space, evaluating such a likelihood function in Maximum Likelihood Estimation is not a trivial problem. Relying on random sampling rather than optimization, the MCMC based on the data augmented posterior provides exact finite sample results rather than relying on asymptotic approximation as well as saving computational costs very significantly. Second, the MCMC approach provides exact finite sample estimates for the individual-level inefficiency measures. Finally, the MCMC approach allows us to formally take parameter uncertainty into account in computing predictive moments and quantiles of any functions of interest, because each parameter is assigned a probability distribution and can easily be integrated out. For example, we can compute $\mathrm{Prob}\left(h(j) > h(j') \middle| Data\right)$, the probability that mean efficiency level of ownership form $j$ is larger than that of ownership form $j'$. Both interpretations and analyses for such functions under the Bayesian approach are transparent and straightforward.

As usual in estimating *translog* cost system, certain regularity conditions on parameters must be imposed in estimation in order to get a well-defined variable cost frontier in terms of economic theory. We impose the following conditions explicitly in estimation. First, the coefficients associated with the interactions among outputs $(\phi' s)$, the interactions among capital inputs $(\psi' s)$, and the interactions among variable inputs' prices $(\tau' s)$, are symmetric. Second, the variable cost frontier in (2) is homogeneous of degree 1 with respect to variable input prices. Lastly, the variable cost frontier is concave in variable input prices. The monotoniticy of the variable cost frontier (nondecreasing in outputs and variable input prices) is verified after estimation. Please see Appendix B for the details of these conditions as well as how we incorporate them in estimation.

## 5. Sample and Variables

Our sample consists of an unbalanced panel of 109 airports around the world, representing different sizes, ownership and institutional arrangements. The data is compiled from various sources including Airport Council International (ACI), the U.S. Federal Aviation Authority (FAA), International Air Transport Association (IATA), and airport annual reports. Some data were obtained directly from the airports. Details on the data are provided in various issues of the ATRS Global Airport Benchmarking Report (for example, Air Transport Research Society, 2007).

To estimate airport cost frontiers, one must first identify outputs that an airport produces and the inputs it uses in producing these outputs. The most commonly used output measures for airports are the number of passengers, the volume of air cargo, and the number of aircraft movements (ATM). Airports typically impose direct (separate) charges for their services related to aircraft movements and the handling of passengers. However, air cargo services are generally handled by airlines, third party cargo handling companies, and others that lease space and facilities from airports. Air cargo services are not considered as a separate output in this research, as airports derive a very small percentage of their income directly from air cargo services. In addition to passenger traffic, cargo traffic and aircraft movements, airports also derive revenues from concessions, car parking, and numerous other services. These services are not directly related to aeronautical activities in a traditional sense, but they are becoming increasingly more important for airports around the world and account for over 60% of the total revenues for many airports. Thus, we consider a third output that consists of revenues from non-aeronautical services. Since non-aeronautical services include numerous items and activities, it is very difficult, if not impossible, to construct an “exact” price index that is consistent across airports in different countries and over time. The Purchasing Power Parity (PPP) appears to be the only viable option that is consistent multi-laterally (across airports in different countries and over time) as a proxy for price index for non-aeronautical outputs, as it adjusts for changes in market exchange rates and changes in real (overall) price levels of different countries over time. A non-aeronautical output index is constructed by deflating the non-aeronautical revenues by the PPP. Inclusion of the non-aeronautical services output also allows us to examine the efficiency implications of airport’s business diversification strategies.

On the input side, we initially considered three variable input categories: (1) labor, measured by the number of (full time equivalent) employees who work directly for an airport operator; (2) purchased goods and materials; and (3) purchased services including outsourcing/contracting out. In practice, however, few airports provide separate expense accounts for the purchased (outsourced) services and purchased goods and materials. Thus, we decided to combine (2) and (3) to form a so-called ‘non-labor variable input”. This non-labor variable input includes all expenses not directly related to capital or labor input costs. The price of labor input is measured by the average compensation per employee (including benefits). Similar to the non-aeronautical output, the non-labor variable input includes numerous items, thus the Purchasing Power Parity (PPP) is also used as a proxy for the non-labor input price. In addition to the variable inputs, two fixed capital inputs are considered: number of runways and total size of passenger terminal area measured in square meters.

Airport efficiency performance are undoubtedly affected by variations in the regulatory and institutional environments in which airports operate, as well as airport characteristics, and operating and market conditions. Some of these factors are beyond the managerial controls of airport operators, thus should be considered as factors affecting the heterogeneity of cost frontier across individual airports. We compile the following variables to control for the observed heterogeneity in cost frontier: percentage of international passengers in total passenger traffic, percentage of cargo traffic in total airport traffic[8], and regional dummy variables.

To examine the effects of ownership forms on airport efficiency, we classify the airports into the following categories that are reflected by ownership dummy variables:

(a) Majority private ownership including 100% private ownership: i.e., private-government mixed ownership with a private majority (private majority);

(b) Government-private mixed ownership with a government majority (government majority);

(c) Government ownership but contracted out to an independent and autonomous management authority via a long term lease (Authority);

(d) 100% government corporation ownership/management/operation (public corp.);

(e) Government ownership and a branch of government operates airport including U.S. city owned airports (government branch); and

(f) Shared ownership by multiple governments including multi-level governments (multi-level government).

(g) Quasi-Public Port Authorities (in the U.S.) that operate both seaports and airports (US port authority).

Table 1 presents some summary statistics of the sample. These summary statistics indicate that there are large variations among the sample airports in terms of their size and business and operating environment. For example, the annual number of airport passengers ranges from 900,000 passengers to 83 million passengers in 2004. Some airports serve only international traffic, whereas others serve mostly domestic passengers. Some airports derive most of their revenue from aeronautical activities,

[8] Measured in terms of Work Load Unit (WLU), a commonly used output measure in the aviation industry that combines passenger and cargo traffic volume. One WLU is defined as one passenger or 100 kg of cargo.

whereas for others, a significant portion of revenues comes from other sources including concession and rentals. Labor cost shares range from 9% to 73%, and average annual employee compensation ranges from US$5,030 to US$101,618 in 2004. It would be interesting to see how such variations would affect the observed performance of the airports.

## 6. Estimation Results and Interpretation

The details of the empirical estimation can be found in Appendices B and C. Under Bayesian approach, estimation results are represented by the posterior distribution of parameters. For each of the parameters of interest, we report the median and the 90% interval (5%-ile and 95%-ile) of its posterior distribution.

### 6.1 Results of the Base Model

Table 2 presents the estimation results of the cost frontier. The first section of Table 2 reports the results of the intercept differentials of the cost frontier across airports and over the years. The variation in the intercept across airports is interpreted as individual heterogeneity in technology, and reflects the effects of the factors beyond airports' managerial control. The cost frontiers of Asian and European airports are significantly higher than those of North American airports. The results of the year dummies indicate upward shifts of the cost frontier in the post- 2001 period, indicating the negative effects of September 11 on airport costs. Finally, the results of $\sigma_v^2$ indicate the existence of a substantial heterogeneity in technology caused by variables other than the observable ones (percentage of international passengers, percentage of cargo, and regional dummies).

Since it is difficult to interpret directly the results of the second order terms in a *translog* function, at the bottom of Table 2 we report the cost elasticities with respect to the three outputs, own price elasticities of the two variable inputs, and the predicted variable input share. The positive cost elasticities and predicted variable input share imply that the monotonicity conditions in outputs and variable input prices are satisfied. Since we impose the concavity condition (concave in variable input prices) in estimation, own price elasticities of the variable inputs have the expected signs.

Finally, the estimation results of the variances and covariance of noise terms indicate that: (a) there are significant variations in costs and labor shares across different airports that are not accounted for by the variables included in our model, justifying the need for a stochastic frontier model; (b) the cost equation and the labor input share equation are negatively correlated; suggesting that it is beneficial to estimate the cost equation and the variable input share equation jointly.

### 6.2. Effects of Ownership Forms on Cost Efficiency

Table 3 summarizes and compares the effects of the seven different ownership forms on airport efficiency. Two alternative specifications of the inefficiency term (the random deviation from the frontier) are estimated with the identical specification of the cost frontier. It is noted that results of the cost frontier parameters between the two alternative models are rather stable, not unduly influenced by alternative specifications of the inefficiency term. Below we discuss and summarize the results from the two alternative models: the Base Model and Model (2).

***The Base Model Results:***

The Base Model is specified by equations (4a) and (4b). Under this model specification, the random deviation of airport *i* with ownership *j* is determined by $\Delta_i = \exp(\Gamma_i), \Gamma_i \sim (\overline{\Gamma}_j, \sigma_\Gamma^2)$. The smaller the deviation is relative to its own cost frontier, the more efficient the ownership form is. The posterior distributions of $\overline{\Gamma}_j$, presented in Column 2 of Table 3, reflect the extent of deviations from the cost frontier under different ownership forms. For example, airports under majority private ownership are more efficient than those under US port authority because the posterior density of $\overline{\Gamma}_1$ lies in the left of the posterior density of $\overline{\Gamma}_8$.

The results from the Base Model can be summarized as follows:

- Airports with the ownership forms of majority private, public corporation, and airport authority are more efficient than those with various forms of government ownership and management (majority government, US city\state, shared government, and US port authority). This suggests that ownership forms in which management can exercise a larger degree of autonomy and face less political influence are helpful to improve the efficiency of airports;
- Among airports with the four government ownership/management forms, those operated by US port authorities[9] are the least efficient;
- The results of the variance of inefficiency parameters $\left(\sigma_{\Gamma}^{2}\right)$ reported in the last row of Table 3 imply that besides ownership forms and other variables included in our cost model, unobserved variables also affect airport efficiency.

***Model 2 - an Alternative Model to Incorporate the Effects of Multiple Airports***

Some metropolitan areas are served by multiple airports, such as New York/New Jersey, Los Angeles, San Francisco Bay area, Chicago, Washington D. C., London, Paris, Rome, etc. These airports may potentially compete against each other. Would the presence of multiple airports influence the effects of ownership forms on airport efficiency? To answer this question, we estimate an alternative model (Model 2) that includes a "Multi-Airport" dummy variable, and another set of ownership form variables. The "Multi-Airport" dummy is given the value of ONE if an airport is in a multiple airport

[9] Airports operated by US port authorities include the three airports in New York/New Jersey area, Boston airport, Seattle airport, Portland airport, and Oakland airport

market, and zero otherwise. To construct the second set of ownership form variables, we re-group the airports in multi-airport markets into two ownership groups: (1) "Corporation" that includes *Majority Private*, *Public Corporation*, and *Airport Authority*: These airports enjoy significant managerial autonomy and are reasonably free from political interference; and (2) "Government" that includes *Majority Government*, *US city/state*, Shared Government, and *US Port Authority*. We also include two interaction terms in Model 2: Multi-Airport * Corporation and Multi-Airport * Government.

The results from Model 2, presented in Column 3 of Table 3, indicate that the presence of multiple airports has no effect on the efficiency of airports under the 'Corporation' ownership forms, whereas the presence of multiple airports has a significant negative effect on the efficiency of airports under the 'Government Group' ownership forms. At first glance, these results appear to be somehow counter-intuitive since a "common-sense" view would be that airports in a multi-airport market faces stronger competition than airports in single airport markets. However, in reality, it is quite common that airports in a metropolitan area with multiple airports are owned and operated by a single airport operator. Such examples include the three airports in New York/New Jersey area, the two airports in Chicago, the two airports in Washington D. C., etc. Even in some cases with different airport operators, airports in the multi-airports areas are often complementary, such as one mainly for domestic passengers and the other one mainly for international passengers. Consequently, the Multi-Airport market variable does not seem to indicate the presence of competition. One possible explanation for the results of Model 2 is that these airports are located in large metropolitan areas, and as such, they are likely to face larger bureaucracy and more political influence from powerful city/state governments, and consequently, become less efficient.

The basic findings on the effects of ownership forms on airport efficiency from the Base Model still hold after controlling the multiple-airport market effects. One implication of the results from Model

2 is that since government-controlled ownership forms in multiple airport cities (Government*Multi-Airport) are less efficient than other airports in similar situation, privatization, corporatization or creation of independent authority for managing an airport in multiple airport city would help improve the efficiency of the airport.

### 6.3 Comparison of Ownership Effects in Single Airport vs. Multiple-Airport Cities:

Table 4 presents the median along with the 5%-ile and 95%-ile of the posterior distributions of efficiency levels[10] for different ownership forms in both single-airport and multiple-airport markets. The posterior medians of the efficiency levels for majority private, public corporation, and airport authority are all above 90% of the frontier in both markets.

The efficiency levels of airports with 'Government' ownership forms are affected by market structure: their posterior distributions shift to the left indicating lower efficiency in multiple-airport markets. The airports operated under shared ownership of multi-level governments and the airports operated by the U.S. port authorities are the least efficient groups in terms of cost efficiency: the posterior medians of their efficiency levels are only about 80% of the frontier in single-airport markets, and about 50% of the frontier in multiple-airport markets.

The findings on the effects of ownership forms on airport efficiency are of course subject to statistical uncertainty. In order to address such uncertainty, we compare the efficiencies between different ownership forms in terms of posterior probability using the results of Model 2 in Table 3. The results of the comparisons are presented in Table 5, and can be summarized as follows:

- There is a 93% probability that airports owned and operated by the U.S. cities/states are more efficient than those owned and operated by the U.S. port authorities in both single-airport and

[10] Recall from Section 3 that the mean efficiency level of all airports under ownership form j is measured by $h(j)$ in Equation 5.

multiple-airport markets; whereas there is an almost 100% probability that airports owned and operated by independent airport authorities are more efficient than those owned and operated by the U.S. port authorities in all markets.

- There is an 89% probability and a 93% probability that airports owned and operated by independent airport authorities are more efficient than the U.S. city/state owned and operated airports in single-airport markets and multiple airport markets, respectively.
- There is a 75% probability that airports owned and operated by operators with private majority than those owned and operated by mixed enterprises with government majority in single-airport markets; and the probability increases to 86% in multiple-airport markets.

### 6.4 Robustness of the Results to Underlying Assumptions

Our data include the year of 2001, and the event of 9/11 is treated as a random shock that led to the increased costs in the years of 2002 – 2004. However, it is also possible that the rising costs at some airports after 9/11 are a result of decreased efficiency. In order to test the 9/11 effects on our results, we re-estimated the models after removing the year 2001 data. The conclusions from the Base Model and Model 2 did not change.

To further ensure the robustness of our results, we also examined the issue of endogeneity between ownership forms and airports' efficiency. This issue arises if governments are more likely to be pressured to privatize or commercialize inefficient airports. After careful considerations, we conclude that the endogeneity issue does not pose any serious problem in our analysis because of the following reasons:

First, as discussed in the introduction, the choice for airport ownership and institutional arrangements is related more to the economy, law, and political systems of a country and/or a region rather than to the efficiency level of individual airports. For example, in reforming airport ownership forms over the last two decades, many governments in Europe, Asia, Australia and New Zealand have fully or partially privatized the major airports in their countries, whereas Canada has chosen to transfer the management and operation of major Canadian airports to independent airport authorities under long-term lease contracts, but retain the ownership of these airports. Some US airports are operated by port authorities mainly because they are located close to major seaports with long history and operated by powerful port authorities. The regional dummy variables are included partly to capture the systematic differences in the choices of airport ownership forms across the regions. If consistent data were available, we would include country-specific indicators of economy, law, and political systems to better control such effects.

Second, the motives for governments to privatize/commercialize airports are diverse, not just for improving operational efficiency. Lack of funding has often been the one of main factors that forces governments to seek creative means to finance the necessary infrastructure improvement and/or expansion. For example, the $2.3 billion Thatcher government received from privatizing the seven major UK airports in 1987 was not negligible, it was as important a motive as improving the efficiency of these airports. Similarly, the expected $2 billion - $3 billion cash windfall is a big reason behind Chicago Mayor Richard Daley's push to privatize Midway Airport.

## 7. Conclusion

In this paper, we estimated a stochastic frontier cost model in *translog* form via a Bayesian approach in order to measure the effects of ownership and institutional forms on the efficiency of airports. Our key empirical findings are: (a) airports owned and/or controlled by majority private firms, autonomous public corporations or independent authorities are more efficient than those owned and/or controlled by government branch (city/state), multiple level governments, or U.S. ports authorities; (b) there is an almost 100% probability that airports controlled/operated by independent airport authorities are more efficient than those controlled/operated by U.S. port authorities, and there is 93% probability that US city/state run airports are more efficient than those operated by U.S. port authorities; (c) there is about 80% probability that airports owned/operated by a majority private firm achieve higher efficiency than those owned/operated by the mixed enterprise with government majority ownership; and (d) airports owned/operated by a Government controlled agencies (US ports authorities, shared government ownership, US city or state government, mixed enterprises with government majority ownership) have significantly lower efficiency in multiple airport markets than in single airport markets. These findings imply the following:

- Countries considering to privatize airports should transfer 100% or a majority ownership to private sector; and should avoid the mixed ownership with government majority in favor of even 100% government owned public firm;
- U.S. should reconsider ownership and management of airports by port authorities;
- Although average efficiency of the airports owned and operated by cities/states are lower than those operated by independent airport authorities, the difference is not statistically significant. As such, this issue needs careful further examinations.

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**Table 1: Summary Statistics [a]**

| | *2001* | *2002* | *2003* | *2004* |
|---|---|---|---|---|
| *Output Measures* | | | | |
| Number of Passengers (million) | 20 (15) | 18 (15) | 18 (15) | 19(16) |
| Number of Aircraft Movements (000's) | 283 (177) | 261 (177) | 258 (177) | 262 (185) |
| Non-Aeronautical Revenue (000's PPP deflated $) | 119 (152) | 112 (150) | 125 (163) | 138 (191) |
| *Variable Inputs* | | | | |
| Number of Employee (000's) | 1.0 (1.8) | 1.1 (2.3) | 1.1 (2.6) | 1.1 (2.6) |
| Non-labor Variable Cost (000's US $) | 91 (115) | 87 (103) | 96 (115) | 100 (121) |
| *Fixed Inputs* | | | | |
| Number of Runways | 2.87 (1.15) | 2.82 (1.16) | 2.90 (1.24) | 2.89 (1.28) |
| Terminal Size (000's Squared Meter) | 170 (162) | 170 (161) | 184 (171) | 187 (179) |
| *Variable Inputs' Prices* | | | | |
| Wage Rate (000's US $) | 54 (28) | 54 (25) | 60 (25) | 63 (28) |
| Non-Labor Variable Input Price (000's US $) | 0.95 (0.15) | 0.92 (0.17) | 0.97 (0.16) | 0.99 (0.19) |
| *Variable Input's Share* | | | | |
| Labor Cost Share | 0.38 (0.14) | 0.39 (0.14) | 0.38 (0.14) | 0.38 (0.14) |
| *Airport Characteristics* | | | | |
| Percentage of International Passengers | 0.29 (0.34) | 0.31 (0.35) | 0.30 (0.35) | 0.32 (0.35) |
| Percentage of Cargo | 0.15 (0.14) | 0.16 (0.14) | 0.16 (0.15) | 0.16 (0.15) |
| *Geographic Distribution of Airports in percentage* | | | | |
| Asian Airports (%) | 9 | 7 | 8 | 10 |
| Australian-New Zealand Airports (%) | 4 | 7 | 7 | 9 |
| European Airports (%) | 17 | 22 | 19 | 21 |
| North American Airports (%) | 70 | 64 | 66 | 60 |
| *Airport Ownership in percentage* | | | | |
| City/State (%) | 32 | 28 | 29 | 27 |
| Public Corporation (%) | 12 | 15 | 14 | 12 |
| Majority Government (%) | 3 | 3 | 1 | 5 |
| US Airport Authority (%) | 28 | 28 | 28 | 25 |
| US Port Authority (%) | 8 | 7 | 7 | 7 |
| Majority Private (%) | 9 | 11 | 13 | 16 |
| Shared Government (%) | 8 | 8 | 8 | 8 |
| *Number of Observation* | 89 | 99 | 96 | 104 |

[a] The numbers in parentheses are the standard errors.

**Table 2: Estimation Results of the Cost Frontier (The Base Model) [a]**

| *Parameters* | *Posterior Median [5%-ile, 95%-ile]* |
|---|---|
| ***Individual and Time Varying Intercept [b]*** | |
| $\overline{\alpha}$ Constant | -0.5990 [-0.7654, -0.4486] |
| $\theta_1$ (% Cargo × constant) | -0.1409 [-0.5300, 0.2527] |
| $\theta_2$ (% International passengers × constant) | 0.2038 [-0.1014, 0.5103] |
| $\theta_3$ (Australia/New Zealand dummy × constant) | -0.4423 [0.6959, -0.1843] |
| $\theta_4$ (Europe dummy × constant) | 0.6518 [0.3501, 0.9652] |
| $\theta_5$ (Asia dummy × constant) | 0.8512 [0.5203, 1.1824] |
| $\theta_6$ (Year 2002) | 0.0721 [0.0423, 0.1018] |
| $\theta_7$ (Year 2003) | 0.0854 [0.0536, 0.1168] |
| $\theta_8$ (Year 2004) | 0.0663 [0.0329, 0.0991] |
| $\sigma_v^2$ (Unobserved heterogeneity) | 0.1007 [0.0837, 0.1216] |
| ***Coefficients of Outputs*** | |
| $\beta_1$ (Passenger) | 0.2018 [0.0076, 0.3932] |
| $\beta_2$ (Aircraft Movements) | 0.2025 [0.0202, 0.3861] |
| $\beta_3$ (Non-Aeronautical Output) | 0.3417 [0.2429, 0.4408] |
| ***Coefficients of Capital Inputs*** | |
| $\lambda_1$ (Runway) | 0.0022 [-0.1247, 0.1288] |
| $\lambda_2$ (Terminal size) | 0.0692 [0.0069, 0.1316] |
| ***Coefficients of Variable Inputs' Prices*** | |
| $\delta_1$ (Wage rate) | 0.3532 [0.3201, 0.3851] |
| ***Coefficients of Interactions among Outputs*** | |
| $\phi_{11}$ (Passenger with Passenger) | 0.4608 [-0.1229, 1.0432] |
| $\phi_{22}$ (Aircraft Movements with Aircraft Movement) | 0.0056 [-0.5579, 0.5639] |
| $\phi_{33}$ (Non-Aeronautical with Non-Aeronautical) | 0.0810 [-0.0766, 0.2393] |
| $\phi_{12}$ (Passenger with Aircraft Movement) | -0.4072 [-0.9122, 0.1009] |
| $\phi_{13}$ (Passenger with Non Aeronautical) | -0.3117 [-0.5747, -0.0488] |
| $\phi_{23}$ (Aircraft Movement with Non Aeronautical) | 0.3331 [0.1152, 0.5536] |
| ***Coefficients of Interactions between Capital Inputs*** | |
| $\psi_{11}$ (Runway with Runway) | 0.0511 [-0.3262, 0.4293] |
| $\psi_{22}$ (Terminal with Terminal) | 0.0751 [-0.0257, 0.1752] |
| $\psi_{12}$ (Runway with Terminal) | -0.2521 [-0.4078, -0.0966] |
| ***Coefficients of Interaction between Inputs' Prices*** | |
| $\tau_{11}$ (Wage rate with Wage rate) | -0.0040 [-0.0160, -0.0003] |

| | |
|---|---|
| ***Coefficients of Interactions between Outputs and Variable Inputs' Prices*** | |
| $\gamma_{11}$ (Passenger with Wage rate) | -0.0810 [-0.1479, -0.0134] |
| $\gamma_{21}$ (Aircraft Movement with Wage rate) | 0.0570 [-0.0109, 0.1252] |
| $\gamma_{31}$ (Non Aeronautical with Wage rate) | -0.0055 [-0.0396, 0.0287] |
| ***Coefficients of Interactions between Outputs and Capital Inputs*** | |
| $\rho_{11}$ (Passenger with Runway) | 0.2286 [-0.1475, 0.6080] |
| $\rho_{12}$ (Passenger with Terminal) | -0.0347 [-0.2136, 0.1440] |
| $\rho_{21}$ (Aircraft Movement with Runway) | 0.2167 [-0.1945, 0.6278] |
| $\rho_{22}$ (Aircraft Movement with Terminal) | 0.0724 [-0.1107, 0.2541] |
| $\rho_{31}$ (Non-Aeronautical with Runway) | -0.1448 [-0.3470, 0.0575] |
| $\rho_{32}$ (Non-Aeronautical with Terminal) | 0.0296 [-0.0598, 0.1197] |
| ***Coefficients of Interactions between Capital Inputs and Variable Inputs' Prices*** | |
| $\zeta_{11}$ (Runway with Wage rate) | 0.0910 [0.0410, 0.1412] |
| $\zeta_{21}$ (Terminal with Wage rate) | -0.0006 [-0.0264, 0.0254] |
| ***Noise variances*** | |
| $\sigma_{\xi}^2$ | 0.0356 [0.0333, 0.0385] |
| $\sigma_{cs}$ | -0.0012 [-0.0021, -0.0004] |
| $\sigma_{\varepsilon c}^2$ | 0.0144 [0.0125, 0.0168] |
| $\sigma_{\varepsilon s}^2$ | 0.0049 [0.0043, 0.0057] |
| ***Elasticities and variable input shares*** [c] | |
| Cost elasticity with respect to aircraft movements | 0.1135 [0.0270, 0.2919] |
| Cost elasticity with respect to passengers | 0.3366 [0.1596, 0.5145] |
| Cost elasticity with respect to non-aeronautical revenue | 0.2905 [0.1971, 0.3844] |
| Own price elasticity of labor inputs | -0.6552 [-0.6977, -0.6219] |
| Own price elasticity of non-labor variable inputs | -0.3672 [-0.4002, -0.3365] |
| Labor input share [d] | 0.3590 [0.3303, 0.3873] |
| **# of observations** | 776 |

[a] In estimation, variable cost, outputs, fixed inputs, and variable input prices are all normalized at their sample means.

[b] The intercept of the cost frontier is specified as $\alpha_{it} = \overline{\alpha} + [\Pi_i, D_{it}]\Theta + \nu_i, \nu_i \sim N(0, \sigma_\nu^2)$, where $\Pi_i$ is the vector of airport's characteristics and $D_{it}$ is the vector of time dummies.

[c] The elasticities and variable input share are evaluated at the sample means of variables.

[d] Non-labor variable input share equals one minus labor input share.

**Table 3: Estimation Results - Efficiency Parameters [a]**

| *Parameters* | *Base Model* | *Model 2* |
|---|---|---|
| $\overline{\Gamma}_1$ (Majority private) | -4.6287<br>[-7.6041, -2.6674] | -4.7205<br>[-7.3802, -2.8804] |
| $\overline{\Gamma}_2$ (Public corporation) | -3.5040<br>[-6.8685, -2.1401] | -3.5839<br>[-7.0752, -2.1797] |
| $\overline{\Gamma}_3$ (Airport authority) | -4.3957<br>[-7.9183, -2.3585] | -3.9756<br>[-6.4890, -2.4356] |
| $\overline{\Gamma}_4$ (Corporation × MultAirport)[b, c] | | 0.2374<br>[-5.9733, 2.0763] |
| $\overline{\Gamma}_5$ (Majority government) | -2.6637<br>[-6.3502, -1.0384] | -3.2477<br>[-6.3296, -1.3452] |
| $\overline{\Gamma}_6$ (US city/state) | -2.1684<br>[-5.9045, -1.2560] | -2.5027<br>[-4.0673, -1.5163] |
| $\overline{\Gamma}_7$ (Shared government) | -1.6043<br>[-3.4218, -0.6897] | -1.8957<br>[-3.8801, -1.1185] |
| $\overline{\Gamma}_8$ (US port authority) | -0.8398<br>[-1.7294, -0.1831] | -1.5871<br>[-2.9813, -0.6590] |
| $\overline{\Gamma}_9$ (Government ×MultAirport) [c, d] | | 1.1179<br>[0.2606, 2.2434] |
| $\sigma_\Gamma^2$ (Variance of $\Gamma_i$ ) [e] | 0.5938<br>[0.3006, 1.2761] | 0.4274<br>[0.2306, 0.9104] |

[a] We report the median and the 90% highest density region [5%-ile, 95%-ile] of the posterior distribution of each parameter. Changing the specification of inefficiency term has negligible effects on estimation results of cost frontier parameters. To save space, we do not report the results of cost frontier across different inefficiency specifications.

[b] Corporation dummy equals to one if the ownership of an airport is majority private, public corporation, or airport authority.

[c] Multi-Airport is a dummy indicating whether an airport is in a multiple airport market.

[d] Government dummy equals to one if the ownership of an airport is US city/state, majority government, US port authority, or shared government.

[e] Our model specifies $\Gamma_i \sim N\left(\overline{\Gamma}, \sigma_\Gamma^2 \mathbf{I}\right)$, with $\mathbf{I}$ denoting the identity matrix.

**Table 4: Efficiency levels Conditional on Ownership Forms (Results of Model 2)** [a]

| | Single-Airport Market | Multiple-Airport Market |
|---|---|---|
| $h(1)$: Majority private | 0.9888<br>[0.9309, 0.9992] | 0.9751<br>[0.7501, 1.00] |
| $h(2)$: Public corporation | 0.9651<br>[0.8670, 0.9989] | 0.9478<br>[0.6957, 1.00] |
| $h(3)$: Airport authority | 0.9766<br>[0.8977, 0.9979] | 0.9334<br>[0.6217, 1.00] |
| $h(4)$: Majority government | 0.9525<br>[0.7184, 0.9977] | 0.8549<br>[0.3347, 0.9347] |
| $h(5)$: US City/State (government branch) | 0.9015<br>[0.7672, 0.9770] | 0.7220<br>[0.4959, 0.9125] |
| $h(6)$: Shared government | 0.8282<br>[0.6089, 0.9735] | 0.5743<br>[0.1693, 0.9016] |
| $h(7)$: US port authority | 0.7732<br>[0.5230, 0.9344] | 0.4543<br>[0.1772, 0.7232] |

[a] Under our model specification, $h_i \equiv \exp(-\Delta_i)$ captures the deviation from the efficiency frontier, and is defined as cost inefficiency. The mean efficiency level under ownership form *j* is measured by $h(j) = \exp(-\overline{\Delta}^j)$, where $\overline{\Delta}^j = E(\Delta_i | Z_i = j)$; $Z_i$ is the vector of ownership dummies and $Z_i = j$ means that the ownership form of airport $i$ is $j$ ( $j = 1,\ldots,8$ ). The efficiency results here are based on the results of Model 2 in Table 3.

**Table 5: Hypothesis Tests for Comparing Efficiency between Ownership Forms [a]**

| | Single-Airport Market | Multiple-Airport Market |
|---|---|---|
| $\Pr(h(j) > h(j'))$: (US City/State > US Port Authority) | 0.93 | 0.93 |
| $\Pr(h(j) > h(j'))$: (Airport Authority > US City/State) | 0.89 | 0.93 |
| $\Pr(h(j) > h(j'))$: (Airport Authority > US Port Authority) | 0.99 | 1.00 |
| $\Pr(h(j) > h(j'))$: **(**Majority Private > Majority Government**)** | 0.75 | 0.86 |

**[a]** The hypothesis tests report the posterior probability measures on whether the mean airport efficiency under ownership form $j$ is greater than the one under ownership $j'$. These posterior probabilities are calculated based on estimation results of Model 2 in Table 3.

## Appendix A. Outline of the Bayesian Approach

Our econometric model can be expressed in the following hierarchical form

$$\ln C_{it} = a_i + X_{it}B + \exp(Z_i\Gamma_i) + \varepsilon_{it}^c \tag{A.1a}$$

$$S_{it} = X_{it}B + \xi_i + \varepsilon_{it}^s \tag{A.1b}$$

$$\alpha_i = \overline{\alpha} + [\Pi_i, D_{it}]\Theta + \nu_i \tag{A.1c}$$

$$\Gamma_i \sim N\left(\overline{\Gamma}, \sigma_\Gamma^2 \mathbf{I_M}\right) \tag{A.1d}$$

$$\xi_i \sim N\left(0, \sigma_\xi^2\right) \tag{A.1e}$$

$$\nu_i \sim N\left(0, \sigma_\nu^2\right) \tag{A.1f}$$

$$\left(\varepsilon_{i1}^c, \varepsilon_{i1}^s, \varepsilon_{i2}^c, \varepsilon_{i2}^s, \ldots, \varepsilon_{iT_i}^c, \varepsilon_{iT_i}^s\right)' \sim N\left(\mathbf{0}_{\mathbf{T_i}}, \Sigma \otimes \mathbf{I}_{\mathbf{T}_i}\right) \tag{A.1g}$$

Since the labor share equation only provides information to estimate a subset of $B$, the entries in $X_{it}$ corresponding to the parameters outside this subset are set as zeros. In (A.1d), the subscript of $M$ denotes the size of $Z_i$. The inference to the unknown parameters is done by sampling from the augmented posterior $p(\Xi, \{\nu_i, \xi_i, \Gamma_i\} | Data)$. The empirical moments of the marginal draws of $\Xi$ are the estimation results of the parameters; the sample mean of the draws of $\nu_i$ is used to measure the unobserved individual effects; since $h_i = \exp(-\exp(Z_i\Gamma_i))$, the draws of $\Gamma_i$ is used to measure individual efficiency level.

The random sampling is done by the Gibbs sampling, in which the full parameter space $(\Xi, \{\nu_i, \xi_i, \Gamma_i\})$ is divided into several components, and the iterations of the Gibbs sampler cycle through the components, drawing each component conditional on the value of all the others. Under certain regularities, the draws from the iteration process converge to the augmented posterior.

The priors on parameters used in estimation are all non-informative and changing the priors has no substantial effects on the posteriors. In order to check the convergence of the random draws, we run the Gibbs sampler from different starting values for the parameters, and plot the time-series of the draws for each of the runs in order to check the convergence. In general, the Gibbs draws converge after about 20,000 draws. To overcome high autocorrelation among the draws, we generate very long chains – 300,000 Gibbs draws, and drop the first 100,000 and use the remaining 200,000 to summarize the posterior means and standard deviations. Tests for Robustness are done by increasing the post-convergence draws to 400,000, and there is very little change in the results.

We specify two airport-specific random terms in our model specification: $(\nu_i)$ controls the variation in cost frontier from unobserved sources (the factors which are not included in $\Pi_i$), $(\Delta_i)$ measures the deviation from the frontier. Greene (2005) refers such specification as true random effects stochastic frontier model. From the estimation results of model 2 in Table 3, we plot the posterior means of $p(h_i|Data)$ and $p(\nu_i|Data)$ to confirm that these two random effects can be separated in estimation. We also find that airport efficiency could be substantially underestimated if the unobserved frontier variation was ignored ($\nu_i = 0$).

The details of the Gibbs sampler and results of the sensitivity analysis can be found in Oum, Yan, and Yu (2007).

**Appendix B. Regularity constraints on the cost frontier**

The following constraints on cost frontier are imposed explicitly in estimation:

1. Symmetric constraints: $\phi_{12} = \phi_{21}, \phi_{13} = \phi_{31}, \phi_{23} = \phi_{32}, \tau_{12} = \tau_{21}, \psi_{12} = \psi_{21}$;

2. Homogeneity constraints: The variable cost frontier is homogeneous of degree 1 with respect to variable input prices, so we have $\delta_1 + \delta_2 = 1$ , $\gamma_{11} + \gamma_{12} = 0$ , $\gamma_{21} + \gamma_{22} = 0$ , $\gamma_{31} + \gamma_{32} = 0$ , $\frac{1}{2}\tau_{11} + \tau_{12} + \frac{1}{2}\tau_{22} = 0$, $\tau_{11} + \tau_{12} = 0$, $\tau_{12} + \tau_{22} = 0$, $\zeta_{11} + \zeta_{12} = 0$, $\zeta_{21} + \zeta_{22} = 0$;

3. Concavity constraint: The variable cost frontier is concave with respect to variable input prices. To impose this constraint in estimation, we first derive the Hessian matrix of the variable cost frontier with respect to variable input prices as

$$\nabla_W^2 C_{it}\left(Q_{it}, W_{it}, X_{it}, t\right) = \begin{pmatrix} \frac{C_{it}}{w_{1it}^2}\left(\tau_{11} + S_{1it}^2 - S_{1it}\right) & \frac{C_{it}}{w_{1it} w_{2it}}\left(S_{1it} S_{2it} + \tau_{12}\right) \\ \frac{C_{it}}{w_{1it} w_{2it}}\left(S_{1it} S_{2it} + \tau_{12}\right) & \frac{C_{it}}{w_{2it}^2}\left(\tau_{22} + S_{2it}^2 - S_{2it}\right) \end{pmatrix} \tag{A.2}$$

where $S$ represents the observed variable input share. As shown by Diewert and Wales (1987), the Hessian matrix is negative semidefinite if and only if $\tau \equiv \begin{pmatrix} \tau_{11} & \tau_{12} \\ \tau_{12} & \tau_{22} \end{pmatrix}$ is negative semidefinite. Combining this with homogeneity constraints, the concavity constraint can be implemented by restricting $\tau_{11} \le 0$.

In estimation, we incorporate the linear constraints associated with symmetry and homogeneity into the cost frontier. We then assign a normal prior truncated above 0, to $\tau_{11}$ to incorporate the concavity constraint. An alternative approach of imposing regularity constraints in estimating flexible functional forms with Bayesian approach can be found in Terrell (1996).

Since the monotonicity properties of the cost frontier (nondecreasing in outputs and variable input prices) could be violated even the concavity constraint is imposed, as suggested by Barnett and Pasupathy (2003), we calculate the cost elasticities with respect to the three outputs, own price elasticities of the two variable inputs, and the predicted variable input share in order to verify the monotonocity properties. As reported in Table 2, they have the expected signs, implying that the monotonicity conditions in outputs and variable input prices are satisfied.

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