5-2016

US airport ownership, efficiency, and heterogeneity

Levent Kutlu
The University of Texas Rio Grande Valley, levent.kutlu@utrgv.edu

Patrick McCarthy
Georgia Institute of Technology

US Airport Ownership, Efficiency, and Heterogeneity

Levent Kutlu*   Patrick McCarthy**

Abstract

All US commercial airports are in the public sector yet not all have the same ownership type. For medium and large hub US airports we use stochastic frontier analysis to analyze the efficiency differences for alternative airport ownership types. We find that while form of ownership may matter for cost efficiency, in general its effect is relatively small. Yet type of public sector ownership does have cost efficiency implications in certain environments. Further, when heterogeneity is not controlled, the results change substantially so that type of ownership matters much more which demonstrates the importance of controlling for cross section heterogeneity.

Keywords: Cost efficiency, stochastic frontier, heterogeneity, airport governance, airport ownership, panel data

JEL Classification: C33, L93, R41

*Department of Economics, Antalya International University, Antalya, Turkey.
E-mail: levent.kutlu@antalya.edu.tr
** School of Economics, Georgia Institute of Technology, Atlanta, GA, USA.
E-mail: mccarthy@gatech.edu

I. Introduction

An April 1, 2014 headline in the NY Times stated: “Report Traces Port Authority’s Flaws to a Crumbling Business Model”, referring to the lane closures on the George Washington Bridge in 2013. The George Washington Bridge is one of six bridges and tunnels managed by the Port Authority of New York and New Jersey (PANYNJ), a joint venture between New York and New Jersey that also manages the region’s seaports, five airports (including JFK International and LaGuardia (New York) and New Jersey’s Newark Liberty airports), and the trans-Hudson rapid rail system (PATH). Of relevance to this paper is that PANYNJ is one of several types of ownership for commercial airports in the US, all of which are in the public sector. Airport or port authorities (as PANYNJ) own and operate some airports while cities, states, and counties own and govern others. And while there have been a number of studies on the economic efficiency of private versus public sector airports, there have been relatively few studies that focus explicitly on the efficiency of alternative forms of public sector ownership associated with US commercial airports. Are port authorities such as PANYNJ, for example, less efficient as suggested by the article’s title or do port authorities embody a level of expertise that enhance cost efficiencies?

This paper reports the results of a stochastic frontier cost model on a panel (1996-2008) of twenty-four medium and twenty-six large hub commercial airports in the US. The analysis contributes to the literature in three specific ways: we analyze the relative efficiency differences across four US commercial airport ownership types (city, county, state, airport authority); we distinguish airport specific heterogeneity due to cost efficiency and, separately, to factors other than efficiency; and we perform a series of counterfactual analyses to analyze the efficiency effects of local ownership, hub size, and multiple airport metropolitan areas.

Based on a single output scenario, where the output is number of departures, our main findings are summarized as follows. First, conditioning on medium hub airports in multi-airport cities, airports owned by city or airport/port authorities have 9.59% (at median) higher variable costs due to cost inefficiency compared to county or state-owned airports. Second, among the medium hub airports owned by the city or airport/port authorities, those in multiple-airport cities have 8.6% (at median) higher variable costs relative to those in single-airport cities.[1] Third, there is not much effect on cost efficiency between medium and large hubs.

Inspired by Hicks' (1935) quiet life hypothesis, we examined the effect of multiple airports in a metropolitan area.[2] For the sample of airports, we find that the median cost efficiency for single-airport and multi-airport cities is 88.2% and 86.9%, respectively, a negligible efficiency difference.[3] In general, when we control for airport specific heterogeneity, the median cost efficiency for the whole sample is 87.6%, which is not very sensitive to ownership type. In sum, it seems that while the form of ownership may not have much effect on cost efficiency individually, their combination may alter cost efficiency levels. The average variable cost differences mostly stem from differences in scale economies for different ownership types. The outcome dramatically changes, however, when we do not control for airport specific heterogeneity. For example, the median cost efficiency for airports with and without local (i.e. city or airport authority) ownership is 80% and 92.6%, respectively. The difference is more dramatic for large and medium hubs (47.3% and 99.5%, respectively). It appears that when not controlling for heterogeneity, the

[1] Cost efficiency is used in the standard stochastic frontier literature language. That is, it is the ratio of the frontier minimum cost to observed cost. A potential reason for such deviation is the principle agent problem that the objectives of administrators may not fully align with cost minimization. Another reason may be optimization mistakes that are done by the decision makers.

[2] Quiet life hypothesis claims that, holding other factors constant, higher competition increases cost efficiency.

[3] Note that efficiency is a relative concept. That is, the efficiency estimates are based on comparison to the best practice. However, since the efficiency is captured by a random component the highest efficiency estimate is not necessarily equals to 100%. When the number of observations is large it may be reasonable to assume that the best practice firm is on the frontier.

intrinsic characteristics of the airports that are not captured by the existing control variables may be misinterpreted as inefficiency/efficiency in costs.

II. Relevant Literature

Arbrate and Erbetta (2010) and Voltes-Dorta and Lei (2013) provide excellent summaries of the increasing body of research on airport costs, efficiency, productivity, and type of ownership. Although similar to the literature cited in these studies, Table 1 complements these literature reviews in focusing on airport ownership and identifying specific results that relate to alternative ownership types. In general, the bulk of the research reported in Table 1, particularly more recent research, indicates that private ownership is more efficient than public ownership. However, this is a broad generalization and the reported studies also indicate that the effect of ownership depends on a number of factors related to the competitive environment.

In the late 1990s and early 2000 period, Vasigh and Haririan (2003), Parker (1999), and Oum, Yu, and Fu (2003) find little effect of privatization on airport operations. Oum, Yu, and Fu (2003) also notes the importance of managerial autonomy in airport efficiency and Vasigh and Haririan (2003) finds that private ownership produced better financial results. Oum, Adler, and Yu (2006) and Oum, Yan, and Yu (2008) find that privatized airports are more efficient than public sector airports but public sector airports are more efficient than airports with a public-private structure. Consistent with this, Botasso, Conti, and Piga (2012) finds no productivity effect associated with mixed ownership forms. Related to these studies, Martin, Roman, and Voltes-Dorta (2009) and Martin and Voltes-Dorta (2011) find that multi-airport systems have higher unit costs because they operate under the presence of non-exhausted scale economies.

Table 1
Airport Ownership Literature

Author(s)	Method	Data sample	Governance Results
Adler, N., Liebert, V. (2014)	DEA	48 German/UK airports, 3 Ausralian airports, 1998-2007	Regardless of ownership form, regulation is necessary to generate competitive forces and mixed ownership is less efficienct regardless of level of competition.
Vasigh, Erfani, and Sherman (2014)	TFP	6 UK, 11 Latin American, 7 US airports, 2000-2010	US public ownership airports more efficient than UK's privatized and Latin America's partially-privatized airports. Market structure/competition may be more important than ownership structure.
Zhao, Q., Choo, Y., and Oum, T. (2014)	SFA	Panel, 54 US and Canadian airports, 2002 - 2008	Airport authorities are 14% more cost efficient and have lower labor shares.
Martin, J., Rodríguez-Déniz, H., and Voltes-Dorta, A. (2013)	SFA (SR)	Panel, 194 airports worldwide, 2007-2009	Higher share of LCC increases cost flexibility; airline dominance increases (decreases) flexibility in US (Europe); Corporatization (outsourcing) enhances (reduces) cost flexibility.
Assaf, A. and Gillen, D.(2012)	TL-BYS SFA	Panel, 73 airports 2003-2008 (Europe, NA, Australia)	Price regulation more important than type of ownership. Regulated firm becoming a private competitor with no regulation yield largest gains.
Assaf, A., Gillen, D. and Barros, C. (2012)	TL-BYS SFA	Panel, 27 airports 1998–2008	Results consistent with idea that a deregulated airline sector combined with a privatized airport sector precludes the need for regulation.
Barbot, C. (2011)	Theory	N/A	Negotiated airport use between the leading airline and the airport (EU case)/long term terminal leases (Australian case) are anti-competitive. Contracts with ‘majority in interest’ clauses with signatory airlines (‘US’ case) do not preclude other airlines in the downstream market.
Bottasso, A., Conti, M. and Piga, C. (2012)	CD	Panel, 24 UK airports 2002–2005	LCCs positively affect TFP. Private/public airport governance structure had no impact on TFP relative to a mixed ownership airport.
Bottasso, A. and Conti, M. (2012)	TL	Panel, 25 UK airports 1994–2005	Relative to public/mixed ownership, private ownership has lower costs but cost advantage fell over time airport competition increased.
Craig, S., Airola, J. and Tipu, M. (2012)	SGM	Panel, 52 US airports, 1979-1992	Airport authorities technically 40% more efficient than city governance but rent dissipation redcues this to a 5% overall cost advantage.
Martín, J. and Voltes-Dorta, A. (2011)	TL (LR)	Panel, 161 airports worldwide, 1991 - 2008	Unexhausted IRS which implies lower cost efficiency for multi-airport systems relative to individual airports.
Martin, J., Roman, C., R., and Voltes-Dorta, A. (2009)	TL SFA (LR, SR)	Panel, 37 Spanish airports, 1991-1997	IRS and technological progress imlies higher unit costs for multi-airport systems.
Fuhr, J., Beckers, T.(2009)	TCE	Case Studies: BOS, JFK, PDX, DTW	Contractual/financing agreements reduce public ownership inefficiency in the US. Revenue bonds/airline agreements enhance efficiency.
Barros, C. and Dieke, P. (2008)	DEA	Panel, 31 Italian airports, 2001-2003	Partially privatized airports contribute to efficiency.
Martín, J. and Voltes-Dorta, A. (2008)	TL	Unbalanced panel, 41 worldwide 1991–2005	Unexhausted IRS implying less cost efficiency at multi-airport systems.
Oum, T., Yan, J., and Yu, C. (2008)	TL (SR)	Unbalanced panel, 109 worldwide 2001–2004	Privatization enhances efficiency but 100% government ownership is preferred to mixed ownership. More than 90% probability that city/state airports more efficient than those owned/operated by airport authorities

Table 1
Airport Ownership Literature (cont'd)

Author(s)	Method	Data sample	Governance Results
Fuhr, J., Beckers, T.	TCE	Case Study: Frankfort,	Private contractual arrangements such as specialized governance
Oum, T. Adler, N., and Yu, C. (2006)	VFP	116 Asia-Pacific, NA, European airpots, 2001-2003	Government majority/multi-level ownership is less efficient than private majority. 100% public ownership more efficent than PPP with government majority.
Vasigh, B., Gorjidooz, J. (2006)	TFP	Panel, 22 airports (US, UK, EU), 2000-2004	Operators of more airports have higher TFP. Productivity effects of ownership and management depends on the competitive environment.
Oum, T., Yu, C., Fu, X. (2003)	OLS	52 World, 99	Ownership structure is not an important determinant, consistent with managerial autonomy having a critical role.
Vasigh, B., Haririan, M. (2003)	OLS	7 BAA airports, 8 US airports	Government airports have better operating efficiency and privatized airports have better financial efficiency.
Parker (1999)	DEA	Panel, BAA. 1979/80 - 1995/96	Privatization had no noticeable impact on technical efficiency
Vasigh, B., Hamzaee, R. (1998)	OLS	Panel, 93 US hub airports, 1985/86 - 1995/96	Airport use agreements are an important for airport profits and capacity utilization. Compensatory airport use agreements add most to profitability.

* See Appendix I for definition of acronyms.
.

The general result that privatization enhances efficiency relative to public sector ownership is a 'proof of concept' result, consistent with economic theory. In order to better understand the relationship between types of airport ownership and efficiency, there is a growing body of research that is looking at underlying characteristics of specific types of airport ownership. Two avenues of research focus on regulation and airport use agreements.

Assaf, Gillen, and Barros (2012) finds that airline deregulation (i.e. a competitive airline sector) combined with a competitive airport sector precludes the need for airport regulation. Consistent with this, Assaf and Gillen (2012) finds that price regulation is more important than airport ownership per se. Adler and Liebert (2014) also highlights the importance of a competition and finds that regulation, regardless of ownership type, is necessary to ensure a competitive environment. And Vasigh, Erfani, and Sherman (2014) argues that market structure and competition may be more relevant for productivity and efficiency compared with ownership structure.

In a theoretical paper on airport use agreements, Barbot (2011) explores the predominant types of use agreements, finding that negotiated agreements with the leading airline and long term leases are anti-competitive whereas majority in interest agreements with signatory airlines are relatively more competitive. Arguably, these results are consistent with Martin, Rodriguez-Deniz, and Voltes-Dorta (2013) that find airline dominance to increase cost flexibility in the US but decrease cost flexibility in Europe. Vasigh and Hamzaee (1998) empirically analyzes use agreements in the US and finds that these increase airport profits and capacity utilization. And more recently, Fuhr and Beckers (2009) finds that contractual financing agreements at US airports reduce public ownership inefficiencies. To the extent that these agreements create greater airport competition, this result may help explain Bottasso and Conti's (2012) finding that the cost advantage of private sector airports has fallen over time.

US airports, all of which are in the public sector, are the focus of the present research and builds upon a few other studies that analyze costs and productivity at US or North American airports. Zhao, Choo, and Oum (2014) examines the effect of ownership on efficiencies of North American (i.e., American and Canadian) airports which includes two basic forms of airport ownership, airport authority and government-owned (which for the US includes city, county, and state). The study finds that, on average, airport authorities are 14% technically more efficient than airports operated by the public sector.

Craig, Airola, and Tipu's (2012) analyzes two types of public ownership, airport authorities and city-owned. Consistent with Zhao, Choo, and Oum (2014), the study finds that airport authorities are 40% technically more efficient than city airports. However, the study also finds that labor and materials inputs at airport authorities capture the bulk of these savings leading to a net cost advantage over city ownership of less than 5%.

Adding to the literature, this study uses stochastic frontier analysis to analyze the cost efficiency implications of public sector ownership for 50 large and medium hub airports in the US. In addition to including all types of commercial airport ownership – city, county, state, and authority – this study includes multiple-airport systems. A modeling contribution is that the analysis explicitly controls for airport specific heterogeneity. This is important because, in the absence of such controls, differences across airports may be due to factors other than efficiency. That is, efficiency estimates may incorrectly capture airport specific heterogeneity.

III. Econometric Model for Cost Function and Efficiency Estimation

Consistent with Aigner, Lovell, and Schmidt (1977) and Meeusen and van den Broeck (1977), our approach relaxes the full efficiency assumption of neoclassical production theory and treats inefficiency as an unobserved component by adding to the traditional two-sided error term v_{it} a one-sided error term $u_{it} \geq 0$ that captures inefficiency. Our stochastic translog variable cost function is

(1) $$\ln VC_{it} = \ln VC_{it}^{*} + u_{it} + v_{it}$$

where VC_{it}^{*} is the deterministic part of variable cost when the airport is fully efficient and is a function of output, input prices, and a quasi-fixed factor of production. In Section IV where we describe our data and Section V where we present estimation results, the specific variables used in our empirical model will be discussed. We assume that u_{it} and v_{it} are independent and that the two sided error term, v_{it}, is uncorrelated with the regressors.[4] When $u_{it} = 0$, the airport reaches the minimal cost level and is considered to be fully efficient. For this analysis, we assume $u_{it} \sim N^{+}(0, \sigma_u^2(z_{it}))$, where N^{+} is the half-normal distribution, z_{it} is a vector of exogenous variables determining the distribution of u_{it}, and $\sigma_u^2(z_{it}) = \exp(z_{it}^{'}\beta_u)$. In addition, we assume that $v_{it} \sim N(0, \sigma_v^2)$ where $\sigma_v^2 = \exp(\beta_v)$.[5]

Conventional cost function estimation includes input share equations in order to improve statistical efficiency. In a SFA setting, this might raise concerns because the u_{it} term captures the combined effect of technical and allocative efficiency, and a misallocation of inputs (i.e. allocative inefficiency) might affect input share equations in a non-trivial way. Kumbhakar and Wang (2006) demonstrate that directly modeling allocative inefficiency from the cost minimization problem generates a complicated form of heterogeneity which can bias the parameter estimates, i.e. u_{it} in Equation (1) is heteroskedastic even when the allocative inefficiency is modeled as homoscedastic in the cost minimization problem.

As this is an unresolved issue in the SFA literature, we model overall inefficiency in a reduced form framework. That is, we model the cost of inefficiency, u_{it}, directly rather than modeling misallocation of inputs at the cost minimization stage. Equation (2) gives the system of equations and distribution assumptions for our empirical model,

[4] See Kutlu (2010), Karakaplan and Kutlu (2015), and Kutlu (2016) on relaxing the exogeneity assumption.
[5] See Battese and Coelli (1992, 1995) for earlier studies using this type of specification in stochastic frontier analysis.

$$\begin{aligned}(2) \qquad & \ln VC_{it} = \ln VC_{it}^{*} + u_{it} + v_{it} \\ & S_{it} = S_{it}^{*} + w_{it}\end{aligned}$$

$$u_{it} \sim N^{+}(0, \sigma_u^2(z_{it}))$$

$$v_{it} \sim N(0, \sigma_v^2)$$

$$w_{it} \sim N(0, \Sigma_w).$$

where S_{it} and S_{it}^{*} are vectors of observed and optimal input shares, respectively. Parameter estimates are obtained by maximizing the log-likelihood function $\ln L = \sum_{i,t} \ln L_{it}$, where the log-likelihood value for unit i at time t corresponding to Equation (2) is:

$$(3) \qquad \ln L_{it} = const. - \ln \sigma_S + \ln \Phi\left(\frac{\varepsilon_{it}\lambda}{\sigma_S}\right) - \frac{1}{2}\ln\frac{\varepsilon_{it}^2}{2\sigma_S^2} - \frac{1}{2}\ln|\Sigma_w| - \frac{1}{2} w_{it}^{'}\Sigma_w^{-1} w_{it}$$

Φ is the cumulative distribution function for the standard normal distribution, $\varepsilon_{it} = u_{it} + v_{it}$, $\sigma_S^2 = \sigma_u^2 + \sigma_v^2$, $\lambda = \sigma_u / \sigma_v$, and $\sigma_u^2(z_{it}) = \exp(z_{it}^{'}\delta)$. The z_{it} vector is a set of explanatory variables that induce heteroskedasticity. $Eff_{it} = E[\exp(u_{it}) \mid \hat{\varepsilon}_{it}]^{-1}$ provides an estimate of cost efficiency, where $\hat{\varepsilon}_{it}$ is the estimate of $\varepsilon_{it} = u_{it} + v_{it}$.

Efficiency and Heterogeneity

In recent SFA analyses (focused on the U.S. banking industry) Almanidis (2013) and Almanidis, Karakaplan, and Kutlu (2015) showed that the efficiency estimates under the assumption that all firms share the same technology differed considerably from those obtained from models assuming multiple technology groups.[6] Hence, if there are technological (and other

[6] Here, technology refers to the production/cost frontiers. In particular, two productive units belong to the same technology group if the parameters representing their production abilities are the same. Airports are complex enterprises that reflect diverse technologies. For example, the FAA airports have design standards that vary by size

productive unit specific) differences and such differences are ignored, then a relatively efficient firm with less advanced technology can be misinterpreted as less efficient than its actual efficiency level. For example, comparing the government institutions with private institutions under the assumption that they share the same technology/frontier might be inappropiate.

Only recently has the SFA literature begun to address the heterogeneity among productive units that is due to factors other than inefficiency. One approach, as noted above, to capture heterogeneity due to technological differences includes technology-group specific dummy variables which, for our variable cost function model, implies that the technological differences are captured by parallel shifts in the cost frontier. A more general way to model different technologies would assume a full set of different parameters for each technology group but this has significiant data implications. A second approach (Barros (2008) models heterogeneity by a random effects model.[7]

And a third approach captures heterogeneity unrelated to inefficiency by including fixed effects dummy variables (Greene 2005a, 2005b). Greene calls this estimator the true fixed effects estimator. Given that the first approach may not be sufficient to capture airport specific heterogeneity and given the greater potential for additional endogenerity in the random effects model, the present study follows Greene's fixed effects specification for controlling heterogeneity

---

and weight of aircraft, mix of aircraft using the airport, altitude, and environmental impacts U.S. DOT, FAA, Advisory Circular AC No: 150/5325-4B, July 1, 2005). Further, adoption of new technologies (e.g. NextGen) will not occur simultaneously for all airports. Other examples include airports' land use decisions in the runway protection zone. Airports must coordinate with the FAA Office of Airports regarding land use and structures (e.g. schools), recreation, transportation (e.g. rail and parking), and fuel and hazardous materials storage (FAA Memorandum, September 27, 2012), all of which reflect a rich mix of technologies. In our empirical model, these and other technology differences are captured by the productive unit specific dummy variables. Hence, the productive units share the same parameter values except the constant term (i.e., fixed effects).

[7] If the heteroegeneity is correlated with the inefficiency term or regressors, the random effects model will produce inconsistent parameter and efficiency estimates. This implies that random effects models, in stochastic frontier framework, are more prone to a potential endogeneity problem compared with the conventional random effects models. That is, the error term for efficiency introduces additional sources of endogeneity.

unrelated to inefficiency. That is, we include panel unit specific dummy variables when modelling $\ln VC_{it}^{*}$. This is one of the other differences between our study and those of Zhao, Choo, and Oum (2014) and Craig, Airola, and Tipu (2011), which do not control for such heterogeneity.[8] Hence, in theory, airport specific heterogeneity may have biased these studies' efficiency estimates in a non-systematic way. In the empirical section, we present evidence supporting such biases for the cost efficiency estimates for US airports.

IV. Sample and Data Sources

The sample for the analysis includes all medium and large hub airports in the contiguous United States for the thirteen year period 1996 – 2008 and for which data were consistently available during the period. Appendix II identifies the airports included in the analysis, the airport's hub status, whether the airport is part of a multi-airport system and, if so, whether airport ownershlip is common across airports.[9]

The output measure for the study is airline departures.[10] The Bureau of Transportation Statistics (http://www.transtats.bts.gov), the FAA (Compliance Activity Tracking System (CATS, http://cats.airports.faa.gov) and the National Flight Data Center (http://nfdc.faa.gov) provided data on airline departures and airport operating costs, runways and ownership, respectively. For the analysis, operating expenses (i.e. variable costs) comprise expenditures on three inputs: 1) labor; 2) contracting, repair/maintenance; and 3) general airport operations. Labor costs include

[8] Zhao, Choo, and Oum (2014) include a Canada dummy variable.

[9] The sample covers large and medium airports in the contiguous US and all but one large hub and twenty-four of thirty-two medium hubs in the contiguous US. In 2008, all primary and non-primary commercial service airports in the contiguous US accounted for 88.5% of all enplanements. Airports in this sample account for 79.3% of all enplanements in the contiguous US. For more information about the data set see McCarthy (2014).

[10] We also estimated a model using passengers rather than departures as the output measure. In general, the results were similar. More details will be provided when we present estimation results in Section V.

expenditures on wages/salary, benefits and pensions to airport employees; contracting, maintenance, and repair costs include expenditures on supplies and materials, repairs and maintenance, and contractual services (e.g. management, financial, engineering, firefighting); and general airport operations costs include expenditures on communications and utilities costs, insurance costs and claims, and small miscellaneous expenses.[11]

Estimating cost functions requires data on input prices which are rarely available. This study is no exception as the FAA does not provide these data and there are no data series on airport wages, contracting/maintenance and repairs, and airport operations, whether by airport or MSA. However, there do exist national price indices for each input and there are MSA regional price indices. Using national and MSA price indices, we adopted a methodology to estimate airport-specific input prices that included the following steps: 1) collect national price indices for each of the inputs for 1996-2008; 2) adjust for MSA regional price differences which generates price variation across geography and time and normalize to 2005; and 3) use the GDP deflator (2005 = 100) to convert costs to real costs and nominal price indices to real price indices.[12]

The quasi-fixed factor in the analysis is the Effective Number of Standard Runways ($ENSR_{it}$), defined as $ENSR_{it} = \sum_{r} (Length_{rit})(Width_{rit}) / 1{,}500{,}000$, i.e. total runway capacity divided by capacity for a 10,000’ by 150’ runway, which can generally accommodate any size commercial aircraft. At the mean, the sample airports had 3.5 actual runways and 3.13 ENSRs.

---

[11] For a more complete definition of these categories, see U.S. DOT, FAA, Advisory Circular AC No: 150/5100-19C, April 19, 2004.

[12] Bureau of Labor Statistics, U.S. Department of Labor, Consumer Price Index, CPI Databases, http://www.bls.gov/cpi/data.htm (series BBLD--, Material and supply inputs to nonresidential building construction). Bureau of Labor Statistics, U.S. Department of Labor, Occupational Employment Statistics (http://www.bls.gov/cew/data.htm). The basis for the MSA price indices is NAICS classification data from QCEW aggregate level 40 (Total MSA Covered). The adopted methodology introduces a measurement error in the price variables, biasing the estimated coefficients towards 0 to the extent that there is large variability in the measurement error (Greene, 2000).

Finally, the model controls for other factors that studies have found to affect airport costs. The share of international departures, defined as the ratio of number of international departures and total number of departures for an airport, accounts for additional costs associated with international flights. And the share of freight, defined as the ratio of freight weight and the sum of freight and passenger weight (assuming that a passenger (along with their luggage) is equivalent to 220 pounds of cargo), captures the extent to which cargo operations affect airport costs. In addition, the FAA CATS provides data on non-aeronautical revenues that the airport derives from parking and retail activities. The model includes two variables, the share of total non-aeronautical revenues from parking and retail activities, to reflect these terminal service activities.[13]

Table 2 provides descriptive statistics for airport departures, costs, input shares, price indices, and some control variables.[14] The analysis includes four ownership categories, city (36%), airport/port authority (44%), county (16%), and state (4%). For the full sample, Table 2, provides descriptive statistics for departures, in total, by ownership, and whether the airport is part of a multiple airport system, as well as total costs, input shares and the quasi-fixed capital.

For the sample as a whole, airports handled an average 129,368 departures and incurred $111.76 million in costs to operate the airport and conduct its varied activities. Airports expended on average 37.9%, 39.8%, and 22.3% of operating costs on personnel, contractual/maintenance, and general operations (i.e. all other operating expenses). As expected, there was greater variation in departures, costs, and cost shares across airports than across time. On the other hand, there was

[13] Rather than including these variables to control for the effects of cargo and non-aeronautical terminal activities, an alternative approach specifies cargo (or cargo-related variable) and non-aeronautical revenues as airport outputs in a multi-product cost function (e.g. Oum, Yan, and Yu (2008), Botasso and Conti (2012)). When estimating a SFA model with airport fixed effects, a single output with control variables for cargo and non-aeronautical was more robust than a multi-output specification.

[14] There are 649 rather than 650 observations in the sample because the Bergstrom International Airport in Austin, Texas was not operational until 1997.

Table 2
Descriptive Statistics, 1996 – 2008
50 Medium and Large Hub Airports

		# Obs		Mean	Std Dev
Full Sample	**Total Departures**	649		129,368	96,154
Ownership Type	City	233		172,253	128,226
	County	104		103,042	68,850
	State	26		73,144	34,860
	Airport/Port Authority	286		109,114	57,975
Airport System	Multiple	195		153,846	117,993
	Separate Ownership	104		131,732	120,837
	Joint Ownership	91		179,118	109,949
	Single	454		118,854	83,033
Hub Size	Large	338		185,030	97,660
	Multiple Airport System	143		195,691	111,241
	Medium	311		68,874	43,690
	Multiple Airport System	52		38,770	9,665
	Total Operating Costs, 2005 $	649	$	111,762,040	109,811,593
Ownership Type	City	233	$	115,084,391	109,863,776
	County	104	$	109,881,254	104,794,281
	State	26	$	63,357,216	42,631,047
	Airport/Port Authority	286	$	114,139,731	115,038,850
Airport System	Multiple	195	$	191,503,850	156,111,587
	Separate Ownership	104	$	142,225,268	143,846,183
	Joint Ownership	91	$	247,822,229	151,125,828
	Single	454	$	77,511,703	53,847,237
Hub Size	Large	338	$	173,738,797	121,498,558
	Multiple Airport System	143	$	249,657,671	143,117,002
	Medium	311	$	44,404,665	20,469,768
	Multiple Airport System	52	$	31,580,843	10,758,321
	Cost Shares				
	Contractural, Repair/Maintenance	649		39.8%	13.7
	General Airport Operations	649		22.3%	13.7
	Personnel	649		37.9%	12.2
	Real Price Indices (2005 = 100)				
	Personnel	649		97.37	6.43
	Airport Operations	649		90.17	11.8
	Contractural, Repair/Maintenance	649		92.39	13.16
	Quasi-Fixed Capital				
	Equivalent Number of 10,000' x 150' runways	649		3.128	1.609
Across Airports	**Total Departures**	50		129,368	337,893
`	**Total Operating Costs, 2005 $**	50		111,762,040	386,647,556
	Cost Shares				
	Contractural, Repair/Maintenance	50		39.80%	41.7
	General Airport Operations	50		22.30%	35.1
	Personnel	50		37.90%	38.7
Across Time	**Total Departures**	13		129,368	107,103
	Total Operating Costs, 2005 $	13		111,762,040	114,511,544
	Cost Shares				
	Contractural, Repair/Maintenance	13		39.80%	25.2
	General Airport Operations	13		22.30%	29.4
	Personnel	13		37.90%	8.0

greater variation in prices across time than across airports.[15]

From Table 2, the predominant form of ownership for airports with the most departures is city ownership, with an average of over 170,000 departures. Airport authority and county ownerships are similar in terms of departures handled (109,114 and 103,042 respectively) and larger than state-owned airports (73,344). On the cost side, however, average operating costs at airports under city ownership are very similar to those with airport authority and county ownership types ($115 million versus $114 and $109 million) even though a city handles a significantly higher number of aircraft departures (e.g. 57.8% relative to an airport authority).

Table 2 also reports departure movements and costs for multi-airport systems where, on average, an airport as part of a multi-airport system handles more than the sample average number of departures. But this also depends on whether the airport is jointly governed. An airport in the sample that is part of a multi-airport system under common or joint ownership handles nearly 180,000 departures in comparison with 131,732 departures that an airport handles when part of a multi-airport system that is not under joint ownership. Whereas an airport under common ownership handles 35% more departures, these airports have 74.2% higher operating expenses, suggesting diseconomies associated with joint ownership.

Significant operating and cost differences also exist between large and medium hub airports. The average number of departures at large hubs is 2.7 times greater, 185,030 versus 68,874 at medium hub airports. But large hub airports incur costs that are nearly 4 times higher than medium hubs, $173.7 versus $44.4 million. Accentuating this difference even more, a large hub airport that is part of a multi-airport system handles five times as many departures than a medium hub counterpart but it does so at nearly nine times the cost ($249.7 versus $31.6 million).

[15] The standard deviation of the real price of personnel, contractual/maintenance, and general operations was 6.29, 1.69, and 1.74 across airports but 39.8, 96.5, and 86.5 across time.

V. Estimation Results

Table 3 reports three sets of maximum likelihood estimation results: 1) a Benchmark model, which includes fixed effects that controls for airport specific heterogeneity; 2) a No-fixed-effects model, which doesn't include fixed effects; and 3) a Passenger model, which controls for airport specific heterogeneity but number of passengers as the output measure.[16] In each model, Contractual, Repair/Maintenance is the input share equation dropped. From the table, the explanatory variables that induce heterogenerity (the z_{it} vector in Section III) includes a constant term, the quasi-fixed factor of production ($\ln k_{it}/\bar{k}$) and its square, a time trend and its square, and dummy variables for large hub, local airport ownership, presence of multiple airports in the geographic area, and joint ownership where the same entity (e.g. New York-New Jersey Port Authority) owns and is responsible for the operations.[17]

A priori, the models satisfy linear homogeneity in prices and factor price symmetry. In the benchmark model, the monotonicity and concavity conditions are satisfied at almost all points (3 violations out of 649 observations).[18] Compared to conventional cost function estimation, regularity conditions are more important for the stochastic frontier models. Sauer, Frohberg, and Hockmann (2006) note that theoretically inconsistent frontiers over- or understate the inefficiency, which could result in counterproductive policy measures. Without controlling for heterogeneity by airport fixed effects, as suggested by Greene (2005), the regularity conditions are violated (about 13.1% (85/649) violation rate in our case).[19] Moreover, the likelihood ratio test rejects the

[16] See the Appendix I for more details about variables.
[17] Output and input prices were demeaned using each airport's average for the sample period. Demeaning for the quasi-fixed factor was based upon the sample average due to limited variation in runway capacity across airports.
[18] Zhao et al.'s (2014) stochastic frontier analysis does not comment on regularity conditions and concavity of the estimated function. Craig et al.'s (2005) symmetric generalized cost function has the property of global concavity.
[19] One potential issue for Greene's (2005) true fixed effects approach, where heterogeneity is captured by panel unit dummies, is that the parameter estimates may be subject to so called incidental parameters problem. Belotti, Daidone, Ilardi, and Atella (2013) argues that this approach may be acceptable when the length of the panel is at least 10. Moreover, Belotti and Ilardi (2014) argues that when the length of the panel is 10 this model behaves quite well. When

Table 3: Stochastic Frontier Estimation Results*

	Benchmark			No-Fixed-Effects			Passenger		
Parameter	**Estimate**	**Std Err**	**Pr>|t|**	**Estimate**	**Std Err**	**Pr>|t|**	**Estimate**	**Std Err**	**Pr>|t|**
Constant	17.7705	0.0436	0.0000	17.7856	0.0647	0.0000	17.7715	0.0330	0.0000
q **(Departures)**	0.4609	0.0806	0.0000	0.5541	0.2580	0.0317	0.6174	0.0888	0.0000
q^2	0.0828	0.1941	0.6696	-1.3969	0.6463	0.0307	-0.0776	0.3222	0.8097
k **(ENSR)**	-0.0362	0.1295	0.7798	0.8369	0.0375	0.0000	-0.0095	0.0678	0.8888
k^2	-0.8749	0.4289	0.0414	0.9187	0.0857	0.0000	-0.7397	0.2665	0.0055
$q*k$	-0.3591	0.1001	0.0003	-0.3820	0.2822	0.1758	-0.2225	0.0951	0.0194
l **(Personnel Price)**	0.3854	0.0047	0.0000	0.3868	0.0047	0.0000	0.3853	0.0047	0.0000
e **(Operations Price)**	0.2195	0.0053	0.0000	0.2189	0.0053	0.0000	0.2198	0.0053	0.0000
l^2	-0.1198	0.0609	0.0494	-0.0701	0.0624	0.2616	-0.1375	0.0581	0.0179
e^2	-0.6855	0.1143	0.0000	-0.6490	0.1147	0.0000	-0.7059	0.1050	0.0000
$l*e$	0.3570	0.0662	0.0000	0.3158	0.0671	0.0000	0.3710	0.0606	0.0000
$l*q$	-0.0546	0.0269	0.0422	-0.0414	0.0269	0.1245	-0.1108	0.0335	0.0009
$e*q$	0.0096	0.0309	0.7552	-0.0002	0.0310	0.9956	0.0492	0.0375	0.1891
$l*k$	0.0641	0.0093	0.0000	0.0687	0.0094	0.0000	0.0642	0.0093	0.0000
$e*k$	-0.0152	0.0106	0.1522	-0.0165	0.0106	0.1199	-0.0150	0.0106	0.1578
$q*Local$ **Ownership**	-0.3419	0.0591	0.0000	-0.2288	0.2534	0.3666	-0.2710	0.0672	0.0001
$k*q*Top10ENSR$	0.4285	0.2181	0.0494	-0.4080	0.6658	0.5400	-0.1124	0.2837	0.6920
q*Large Hub	0.0625	0.0665	0.3474	0.0244	0.2600	0.9251	-0.0021	0.0745	0.9780
Share of int'l departures	0.7756	0.2181	0.0004	-0.0490	1.6051	0.9757	0.0730	0.2271	0.7479
Share of freight	0.0612	0.1168	0.6000	-1.1594	0.3565	0.0011	0.0825	0.1024	0.4205
Parking (% in Revenue)	-0.2427	0.1002	0.0154	0.3251	0.3627	0.3700	-0.1942	0.1106	0.0792
Retail (% in Revenue)	0.1700	0.0952	0.0740	0.7089	0.7289	0.3308	0.2615	0.0990	0.0082
Year Dummy Variables									
D1998	0.0236	0.0217	0.2763	-0.0601	0.0772	0.4366	0.0161	0.0289	0.5777
D1999	0.0868	0.0196	0.0000	-0.0574	0.0780	0.4619	0.0647	0.0238	0.0065
D2000	0.0891	0.0188	0.0000	-0.0910	0.0792	0.2505	0.0372	0.0218	0.0875
D2001	0.1188	0.0198	0.0000	-0.1250	0.0874	0.1529	0.0918	0.0216	0.0000
D2002	0.1541	0.0271	0.0000	-0.0405	0.0932	0.6639	0.1511	0.0283	0.0000
D2003	0.2020	0.0248	0.0000	-0.0154	0.1011	0.8790	0.2081	0.0259	0.0000
D2004	0.1766	0.0242	0.0000	-0.0546	0.1046	0.6016	0.1636	0.0251	0.0000
D2005	0.1777	0.0259	0.0000	-0.0495	0.1025	0.6287	0.1508	0.0245	0.0000
D2006	0.1636	0.0247	0.0000	-0.0547	0.1009	0.5880	0.1300	0.0260	0.0000
D2007	0.1904	0.0254	0.0000	-0.0346	0.1065	0.7453	0.1455	0.0217	0.0000
D2008	0.1941	0.0239	0.0000	0.0004	0.1046	0.9971	0.1577	0.0226	0.0000
$\sigma^2(u)$									
Constant	-1.1832	0.0222	0.0000	-10.5313	0.0770	0.0000	-1.1356	0.0210	0.0000
Hub	-0.7636	0.1253	0.0000	9.5826	0.2512	0.0000	-0.6367	0.1291	0.0000
Local	0.4537	0.0260	0.0000	0.4081	0.2774	0.1412	0.3303	0.0380	0.0000
MAP (Multiple Airport)	-0.1233	0.0695	0.0759	1.5728	0.0097	0.0000	-0.2293	0.0649	0.0004
MAPJO (Jointly Operated)	0.2971	0.1599	0.0631	0.0898	0.2072	0.6647	0.0458	0.2116	0.8287
k	0.2344	0.0560	0.0000	-0.8637	0.0249	0.0000	0.3129	0.0703	0.0000
k^2	0.2935	0.1118	0.0086	-1.6092	0.0324	0.0000	0.2960	0.0831	0.0004
t **(Trend)**	-0.5013	0.0100	0.0000	0.0115	0.0117	0.3269	-0.4917	0.0088	0.0000
t^2	0.0280	0.0006	0.0000	-0.0013	0.0016	0.4255	0.0273	0.0006	0.0000
$\sigma^2(v)$									
Constant	-10.3026	0.0221	0.0000	-2.0533	0.0689	0.0000	-10.3430	0.0213	0.0000
Log-likelihood		1405.9			525.5			1420.9	
Median Efficiency		87.6			80.9			87.7	
# of Violations		3/649			85/649			12/649	

*To facilitate reading the table, the first instance of q, k, l, and e identifies the variables name.

---

the length of panel is 15 they mention that the finite sample properties are very good. In our data set the number of time periods is 13, which seems to be reasonably large enough to avoid the effects of incidental parameters problem.

restricted No-Fixed-Effects model at any conventional significance level. Hence, the Benchmark model dominates the No-Fixed-Effects model on theoretical and statistical grounds. We also compared the efficiency estimates from the Benchmark and No-Fixed-Effects models in order to examine the success of the efficiency estimates from the No-Fixed-Effects model. A Kolmogorov-Smirnov test rejects the equality of distributions at any conventional levels. Moreover, the Pearson and Spearman correlations of efficiency estimates are -0.07 and 0.03, which clearly reflects how different the efficiency estimates can be when not controlling for airport-specific heterogeneity.

In Table 3 $l_{it} = \ln L_{it} / \overline{L}_i$ and $e_{it} = \ln E_{it} / \overline{E}_i$ stand for input prices for Personnel and Airport Operations, respectively.[20] The model in Table 3 includes a term that is the product of output measure ($q_{it} = \ln Q_{it} / \overline{Q}_i$) and a dummy variable Local that equals 1 if the city or an airport/port authority owns the airport and 0 otherwise. This captures technological differences that may exist for airports locally governed relative to airports governed at a more aggregate county or state level.[21] Also included in the model is the product of q_{it} and ENSR (the capital measure $k_{it} = \ln K_{it} / \overline{K}$), and Top10ENSR, a dummy variable that equals 1 if the airport is among the top 10 airports in terms of the quasi-fixed factor of production.[22] Without this term the marginal cost estimates for these airports were negative for 4.2% (27/649) of the observations.[23] This may be

[20] These variables are further normalized to assure homogeneity in prices. See Appendix I for further details about acronyms and transformations applied to the variables, i.e., log-demean, demean, or no transformation.

[21] Prior estimations could not reject the null hypothesis that the coefficients for city and airport authority ownership were equal and that state and county ownership types be the reference category.

[22] As mentioned earlier, relative to standard translog models, non-negative marginal costs (i.e., monotonicity with respect to output) and curvature regularity conditions (i.e., concavity with respect to input prices) are more important for stochastic frontier models. Further, a likelihood ratio test based upon the reported model and a model that excluded the product of $q_{it}k_{it}$ and Top10ENSR rejected the null hypothesis that the model omit this term.

[23] We also tried Top5ENSR and Top15ENSR dummy variables, which are dummies for top 5 and top 15 airports. While the median efficiency levels were very close, the regularity condition are violated more than 5.2% and 4.2%, respectively. Moreover, the log likelihood value for Top10ENSR was higher. This is in line with our heuristic choice for top 10 airports.

attributed to the fact that some of the airports have particularly higher capital levels relative to the median airport. This additional term gives us the flexibility to capture this pattern. On average, these airports had 2.7 more ENSRs (5.2 vs. 2.5), a difference which can potentially affect the cost structure.

Two dummy variables model efficiency and joint ownership: a multiple airport dummy variable (MAP) equals 1 if there are multiple airports in the same metropolitan area, 0 otherwise; and a multiple airport joint ownership dummy variable (MAPJO) that equals 1 for metropolitan areas with more than 1 airport and with joint ownership, 0 otherwise. For the sample, areas with joint ownership include Chicago (Midway and Chicago O'Hare), New York-New Jersey (JFK, LaGuardia, Newark), and Washington DC (Washington National and Dulles).

Robustness Checks

In order to check the robustness of our results to choice of output the third model in Table 3 uses passengers rather than departures as the output measure. The results are similar except for some relatively small differences in the output-related variables. For example, the median for returns to capacity utilization were 2.56, lower than the 3.56 using departures.

As a second robustness check, we define MAP in our analysis by the presence of multiple airports in the same metropolitan statistical area. For our sample, a notable exception is Baltimore/Washington International (BWI) which is not part of the Washington metropolitan statistical area but it is only 33 miles driving distance from Washington DC. In order to check the robustness of our results to the definition of MAP variable, we used an alternative multiple-airport variable, MAPalt, that included BWI and Washington the DC airports, San Diego and Long-Beach-Los Angeles, Austin-Bergstrom International and San Antonio, and Indianapolis and

Cincinnati-Northern Kentrucky as part of a multiple airport system. Appendix II identifies the MAPalt variable and Appendix III reports the regression results.[24]

A third robustness check focused on the definition of a hub airport. This analysis uses the FAA definition which identifies a hub airport by the number of annual passenger boardings. Rather than a size-based measure of hub, a competitive-based measure (often used in market analyses) focuses on airlines that have established hub operations at various airports. In exploring this, for all FAA-defined large hubs in the sample, with the exception of Las Vegas, the airport serves as a hub for some airline. To evaluate whether this affects our results, we define an alternative dummy variable for large hubs (HubMkt). The HubMkt variable equals 1 if an airport is a large hub by the FAA definition and also serves as a hub for an airline. By this definition, HubMkt equals 0 for Nevada McCarran (LAS) because this is not a hub airport for any airline. In Appendix III, we report the regression outputs using this variable.[25]The results in Table 3 indicate short run returns to scale, with a median value for the sample equal to 3.56.[26] Own price input demand elasticities are negative and price inelastic for Personnel (-0.94) and Contractual, Repair/Maintenance (-0.83). For General Airport Operations, demand is price elastic (-3.93), which reflects the many and varied types of airport activities in this category. Estimated cross price elasticities indicate that General Airport Operations is a substitute for Personnel and Contractual, Repair/Maintenance but that Personnel and Contractual, Repair/Maintenance are complements in production. Also, the

---

[24] A reviewer correctly noted that BWI, although not in the same metropolitan statistical area, is likely in the same multi-airport market for airline travel. To explore the effects of this, we used distance and popular (i.e.newspaper) accounts of the markets to identify the four groupings.

[25] Although FAA defined and market-based hubs are highly correlated, this is less true for medium hubs. In the sample, twelve medium hubs, by FAA's definition, do not serve as airline or market-based hubs. Using the market-based definition, the reference category for the hub variable is now non-large hubs included in the sample rather than medium hubs.

[26] See Caves et al. (1981) on the relationship between short and long run returns to capacity utilization. The formula for scale economies is: $RTS = \left(1 - \frac{\partial \ln(VC)}{\partial \ln(k)}\right) / \frac{\partial \ln(VC)}{\partial \ln(q)}$ which coincides with long run economies of scale if investment in the quasi-fixed factor is optimal.

coefficients for the time trend and its square in the inefficiency term indicate that during the sample period airport inefficiencies decreased until 2003 and increased afterwards.[27]

Airport Ownership and Heterogeneity

In order to get some understanding of the cost efficiency implications of airport ownership and other operational-related indicators, we identified a benchmark counterfactual and then calculated the impact on costs when one or more indicators are present. Table 4 reports the median percentage change in average variable costs due to cost efficiency under four different scenarios. For each scenario, input prices, departures, and the quasi-fixed factor are set to their actual values. Assumptions on the indicator variables (Hub Size, Local Ownership, Multi-Airport MSA, Multi-Airport Joint Ownership MSA) generate the alternative scenarios. The counterfactual scenarios are:[28]

1. Benchmark counterfactual – To generate the benchmark counterfactual, set all indicator variables to zero. Then calculate the percentage change in median average variable cost due to cost efficiency for those airports whose row indicator equals one and zero, respectively.

   For example, in the first row of Table 4, the dummy variables for Multi-Airport MSA and Large Hub are set to zero. This benchmark counterfactual then compares the median average variable cost for a medium hub airport that not part of a multi-airport system and

[27] The parameters in the inefficiency term, u, are identified through the asymmetric distribution of this random variable. Hence, identification does not solely rely on the means of these variables. Because the coefficients of these variables are significant and the likelihood ratio test favors our benchmark model at 5% significance levels, we prefer to include them in our model. The average efficiency values and patterns of time-effects are similar.

[28] The stochastic frontier estimates for efficiency rely on the assumption that airports minimize costs conditional on a given amount of output. If airports have different sets of incentives (e.g. political as described on page 1) and sacrifice efficiency for other purposes, this would be captured as inefficiency. Thus, underlying our counterfactual analysis is the cost minimization idea. At the same time, however, airport specific dummies may capture differences that may exist in airport objectives.

has a county/state ownership form (i.e. Local Ownership equals 0) with an airport that is a medium hub, not part of a multi-airport system, but with a city/(air)port authority form of ownership (i.e. Local Ownership equals 1);

2. Conditioning counterfactuals – There are three conditioning counterfactuals corresponding to Columns (2) – (4). Calculate the percentage change in medians of average variable costs due to cost efficiency when a particular row indicator (e.g. Large Hub) equals one and zero, as in the above scenario, but now with a conditioning indicator (e.g. Local Ownership, Column (2)) set to one. For example, for the first row and third column (Multi-Airport MSA), Multi-Airport MSA dummy is set to one and Large Hub dummy is set to zero.

Table 4: Changes in the Estimated Average Variable Cost (%)

	Counterfactual Scenarios			
	(1)	(2)	(3)	(4)
		Conditioning Indicators		
Indicator Variable	Benchmark[1]	Local Ownership[2]	Multi-Airport MSA[3]	Large Hub[4]
Local Ownership	-1.02	n/a	9.59	1.56
Multi-Airport MSA	-1.91	8.60	na	2.11
Multi-Airport Joint Ownership MSA	-	-	-	-
Large Hub	-1.22	1.36	2.83	n/a

Benchmark Counterfactual

The benchmark results indicate that none of the four indicator types as a single differentiator, is dominant in cost efficiency.[29] Locally governed airports only have 1.02% lower average variable costs (due to cost efficiency) than county or state-owned airports. And separate ownership of multiple airports within a MSA leads to a 1.91% cost reduction. The MAVC for a

[29] In the Benchmark scenario, the number of observations used to calculate the percentage change is 221, 26, 0, and 39 (i.e., no observations and identified by the '-'s in the table.). For example, the number of observations which are local ownership but not multiairport or large hub is 221. Similarly, the number of observations which are hub but not multiairport or local ownership is 39.

county/state-owned airport that is a large hub and the only commercial airport in the MSA, is only 1.22% lower than a similarly situated medium hub airport.

Conditioning Counterfactuals

The underlying assumptions for Columns (2) – (4) are the same as for the benchmark counterfactuals except that the results are now conditioned on one of the other indicator variables. From the results, we see that the effect of Local Ownership on average variable cost due to cost efficiency changes considerably when the airport is in a multi-airport MSA, -1.02% versus 9.59%. However, the magnitude of change in MAVC (due to cost efficiency) of Local Ownership remains similar (1.56%) when the airport is a large hub. Also, there are mixed results in MAVC of Multi-Airport MSA depending on the type of ownership. Multi-Airport MSA ownership is most (negatively) effective in cost efficiency when accompanied by local ownership (8.6% more variable costs).

Other Results

Table 5 reports the median values for cost efficiency, average variable cost, marginal cost, and efficient marginal cost (the airport's counterfactual marginal departure cost should the airport operate fully efficiently (Kutlu and Sickles (2012)).[30] Efficiency is given as percentages and monetary unit is the US dollar.

For the overall sample, Column (1) indicates that airports have an estimated 87.6% cost efficiency. But depending on hub size and airport ownership, cost efficiency ranges from a low of 85.2% for Multi-Airport Joint Ownership MSA to a high of 88.6% for airports that the county or

[30] Efficient Marginal Cost = Marginal Cost*Efficiency. Note that median of MC and EMC may not come from the same airport-time pair. The percentage difference in MC and EMC medians, ranging from 13%-25% is relatively high but this does not necessarily translate to efficiency differences.

Table 5: Estimated Cost Measures *

Sample Medians

		[1] Cost Efficiency	[2] Average Variable Cost	[3] Marginal Cost	[4] Efficient Marginal Cost
Sample		87.6	784.3	214.9	173.5
Hub Size	Large	87.4	866.9	234.2	203.3
	Medium	88.3	696.3	173.7	129.7
Local Ownership	Yes	87.4	799.5	173.7	139.7
	No	88.6	838.2	574.4	476.2
Multi-Airport MSA	Yes	86.9	1034.0	367.3	299.1
	No	88.2	706.3	174.5	139.0
Multi-Airport Joint Ownership MSA	Yes	85.2	1233.5	344.8	289.2
	No	87.4	949.2	463.7	404.7

* The formula for efficient marginal cost is estimated marginal cost MC_{it} multiplied by cost efficiency $Eff_{it} = E[\exp(u_{it}) \mid \hat{\varepsilon}_{it}]^{-1}$.

state owns. Hence, none of the individual ownership types has a substantial effect on cost efficiency.

The absence of coordinating benefits in multiple airport MSAs is also apparent in Table 5. Jointly governed airports have 30% higher average variable costs relative to separately governed airports.

VII. Concluding Comments

This study aims to add to the growing literature on public sector ownership and its impact on costs. Even though all US commercial airports are in the public sector, not all commercial public sector airports may be equally efficient. The specific form of airport ownership may have implications for technical and cost efficiency. Hence, our interest is to understand the implications of ownership types on efficiency and the importance of airport specific heterogeneity when estimating efficiencies of airports. Following Greene (2005), we use a stochastic frontier model that controls for airport specific heterogeneity via airport fixed effects. This way we illustrate the importance of controlling heterogeneity in the stochastic frontier setting; and in particular for a sample fifty medium and large hub airports in the US.

When estimating our model without controlling for airport specific heterogeneity, median efficiency was 80.9% in comparison with the 87.6% we found when controlling for heterogeneity. And reflecting an improved specification, 0.5% and 13.1% regularity conditions were violated with and without modeling airport specific heterogeneity, respectively. Focusing upon large and medium size hub airports, the benchmark and counterfactual results indicate that: 1) there is less than a 2% improvement in cost efficiency when comparing costs across a single indicator – local versus non-local ownership, multi-airport MSA versus single airport MSA, and large versus medium hub; 2) there is a relatively small decrease in some conditional cost efficiencies. In particular large hubs in locally governed cities and large hubs in multi-airport MSAs have higher average costs than their medium hub counterparts. These cost efficiency differences range from 1.4% - 2.8%; and 3) there is a relatively large 8.6-9.59% difference in cost efficiency for locally governed airports in multi-airport MSAs. Each of the latter two results is robust to the conditioning factor. For example, conditioned on large hub, airports in a multi-airport MSA have 2.1% higher average costs. Conversely, conditioned on a multi-airport MSA, large hubs have a 2.83% higher average cost.

This study's findings complement the findings of a number of prior studies and point to additional avenues of research. Finding no cost difference between city and airport/port authority ownership contrasts with Chao, Choo, and Oum (2014) and Craig, Airola, and Tipu (2012), which find cost efficiencies associated with an airport/port authority form of ownership. Also, from the benchmark results, there is a small 1% cost efficiency difference between city and port authority ownership relative to county or state owned airports. This suggests that studies which combine all forms of public sector ownership into a single index may be an appropriate specification when modeling public versus private sector ownership. Further, this result implies that the regulatory structure in the US airport sector fosters a competitive environment, consistent with works of Adler and Liebert (2014), Oum, Yu, and Fu (2003), and Barbot (2011).

At the same time, the counterfactual analysis identifies specific situations in which local ownership at the city or airport/port authority level does matter and leads to lower cost efficiency. When located in multi-airport MSAs, locally governed airports have average costs that are 8%-9% higher relative to comparable airports in a single airport MSA. This result is consistent with the work of Martin and Voltes-Dorta (2011) and Martin, Roman, and Voltes-Dorta (2009) that found higher unit costs in multi- relative to single airport cities and with coordinating difficulties associated with jointly-run airports such as the New York-New Jersey Port Authority.

The current study raises a number issues for further research. One, expanding the data set to the most recent year and including large, medium, and small hubs would increase the number of observations, which would enable a richer set of empirical specifications. In particular, the conditioning results for multi-airport and jointly governed airports include a small number of airports. Enlarging the sample to include more airports would inform on whether the conditioning effects are representative. Two, and related, this study estimates a relatively high estimate for returns to capacity utilization, consistent with McCarthy (2014) using the same data but higher than estimates from other studies. A richer set of data and analyses would help identify reasons for these differences and is a fruitful area of research as it has important investment and policy implications. Third, this study focuses on forms of ownership. Complementing these data with detailed information the extent to which airport management is outsourced would provide important insights on why alternative forms of ownership affect costs. Fourth, what specific roles do federal, state, and local regulations have in creating a competitive environment and affecting airport operations and costs? Fifth, in our study we model heterogeneity via airport dummies. In general, the heterogeneity may change over time or it may be determined through a particular variable that is "measuring" intrinsic differences of airports (Kutlu, 2015). With our data set such an analysis was not feasible. However, if the data set is extended to have more time periods, such an analysis may provide a more accurate analysis of the relationship between ownership type and efficiency. Last, an underlying assumption is that US commercial airports seek cost efficiency. Understanding the extent to which publicly-owned airports pursue other goals and how this affects cost efficiency by ownership type and vis-à-vis private ownership would provide additional insights on the trade-off between cost efficiency and these other goals.

References

1. Aigner, D., K. Lovell, and P. Schmidt (1997), Formulation and Estimation of Stochastic Frontier Function Models, *Journal of Econometrics* 6, 21-37.

2. Almanidis, P. (2013), Accounting for Heterogeneous Technologies in the Banking Industry: A Time-varying Stochastic Frontier Model with Threshold Effects, *Journal of Productivity Analysis* 39, 191-205.

3. Almanidis, P., M. U. Karakaplan, and L. Kutlu (2015), Are the Banking Authorities Looking at the Wrong End of the Size Spectrum, Unpublished manuscript.

4. Abrate, G. and F. Erbetta (2010), Efficiency and Patterns of Service Mix in Airport Companies: An Input Distance Function Approach, *Transportation Research E* 46, 693–708.

5. Adler, N. and V. Liebert (2014), Joint Impact of Competition, Ownership Form and Economic Regulation on Airport Performance and Pricing, *Transportation Research* A 64, 92–109.

6. Assaf, A. G. and D. Gillen (2012), Measuring the Joint Impact of Governance Form and Economic Regulation on Airport Efficiency, *European Journal of Operational Research* 220, 187-98.

7. Assaf, A. G., D. Gillen, and C. Barros (2012), Performance Assessment of UK Airports: Evidence from a Bayesian Dynamic Frontier Model, *Transportation Research E* 48, 603-15.

8. Barbot, C. (2011), Vertical Contracts between Airports and Airlines, *Journal of Transport Economics and Policy* 45, 277-302.

9. Barros, C. (2008), Technical Efficiency of UK Airports, *Journal of Transport Air Management* 14, 175-78.

10. Battese, G. E. and T. J. Coelli (1992), Frontier Production Functions, Technical Efficiency

and Panel Data: With Application to Paddy Farmers in India, *Journal of Productivity Analysis* 3, 153-69.

11. Battese G.E. and T. J. Coelli (1995), A Model for Technical Inefficiency Effects in a Stochastic Frontier Production Function for Panel Data, *Empirical Economics* 20, 325-332.

12. Belotti, F. and G. Ilardi (2014), Consistent Inference in Fixed-Effects Stochastic Frontier Models, Working paper.

13. Belotti, F., S. Daidone, G. Ilardi, and V. Atella (2013), Stochastic Frontier Analysis Using Stata, *Stata Journal*, 719-758.

14. Bottasso, A. and M. Conti (2012), The Cost Structure of the UK Airport Industry, *Journal of Transport Economics and Policy* 46, 313-32.

15. Bottasso, A., M. Conti, and C. Piga (2012), Low Cost Carriers and Airports' Performance: Empirical Evidence from a Panel of UK Airports, *Industrial and Corporate Change* 22, 745-69.

16. Craig, S., J. Airola, and M. Tipu (2012), General Purpose of Special District Governance? Technical Efficiency vs. Rent Dissipation in Airport Finances, *Public Finance Review* 40, 712-35.

17. Fuhr, J. and T. Beckers (2009), Contract Design, Financiing Arrangements and Public Ownership - An Assessment of the US Airport Governance Model, *Transport Reviews* 29, 459-78.

18. Greene, W. H. (2005a), Fixed and Random Effects in Stochastic Frontier Models, *Journal of Productivity Analysis* 23, 7-32.

19. Greene, W. H. (2005b), Reconsidering Heterogeneity in Panel Data Estimators of the Stochastic Frontier Model, *Journal of Econometrics* 126, 269-303.

20. Hicks, J. R. (1935), Annual Survey of Economic Theory: The Theory of Monopoly, *Econometrica* 3, 1-20.

21. Karakaplan, M. U. and L. Kutlu (2015), Consolidation Policies and Saving Reversals, Working Paper (Available at SSRN: http://ssrn.com/abstract=2607276).

22. Kumbhakar, S. and H. J. Wang (2006), Pitfalls in the Estimation of a Cost Function that Ignores Allocative Inefficiency: A Monte Carlo Analysis, *Journal of Econometrics*, 134, 317-340.

23. Kutlu, L. (2010), Battese-Coelli Estimator with Endogenous Regressors, *Economics Letters* 109, 79-81.

24. Kutlu, L. and R. Sickles (2012), Estimation of Market Power in the Presence of Firm Level Inefficiencies, *Journal of Econometrics* 168, 141-155.

25. Kutlu, L. (2016), Time-Varying True Individual Effects Model with Endogenous Regressors, Working paper (Available at SSRN: http://ssrn.com/abstract=2721864).

26. Martin, J. C. and A. Voltes-Dorta (2011), The Econometric Estimation of Airports' Cost Function, *Transportation Research B* 45, 112-127.

27. Martin, J. C., C. Roman, and A. Voltes-Dorta (2011). Scale Economies and Marginal Costs in Spanish Airports, *Transportation Research* E 47, 238-48.

28. Martin, J. C., H. Rodríguez-Déniz, and A. Voltes-Dorta (2013). Determinants of Airport Cost Flexibility in a Context of Economic Recession, *Transportation Research* E 57, 70-84.

29. McCarthy, P. (2014), US Airport Cost and Production Technology: A Translog Cost Function Analysis, *Journal of Transportation Economics and Policy* 48, 427-447.

30. Meeusen, W. and J. van den Broeck (1977), Efficiency Estimation From Cobb-Douglas Production Function with Composed Error, *International Economic Review* 8, 435-444.

31. Oum, T., N. Adler, and C. Yu (2006), Privatization, Corporatization, Ownership Forms and Their Effects on the Performance of the World's Major Airports, *Journal of Air Transport Management* 12, 109-21.

32. Oum, T., J. Yan, and C. Yu (2008), Ownership Forms Matter for Airport Efficiency: A Stochastic Frontier Investigation of Worldwide Airports, *Journal of Urban Economics* 64, 422-435.

33. Oum, T., C. Yu, and X. Fu (2003), A Comparative Analysis of Productivity Performance of the World's Major Airports: Summary Report of the ATRS Global Airport Benchmarking Research Report—2002, *Journal of Air Transport Management* 9, 285-297.

34. Parker, D. (1999), The Performance of BAA Before and After Privatization, *Journal of Transport Economics and Policy* 33, 133-45.

35. Sauer, J., L. Frohberg, and H. Hockmann (2006), Stochastic Efficiency Measurement: The Curse of Theoretical Consistency, *Journal of Applied Econometrics* 9, 139-165.

36. Vasigh, B., G. R. Erfani, and B. W. Sherman, (2014), Airport Performance and Ownership Structure: Evidence from the United Kingdom, United States, and Latin America, *Journal of Aviation Technology and Engineering*: 4, 40-49.

37. Vasigh, B. and R. G. Hamzaee (1998). A Comparative Analysis of Economic Performance of U.S. Commercial Airports, *Journal of Air Transportation Management* 4, 209-216.

38. Vasigh, B. and M. Haririan (2003), An Empirical Investigation of Financial and Operational Efficiency of Private versus Public Airports, *Journal of Air Transportation* 8, 91-110.

39. Voltes-Dorta, A. and Z. Lei (2013), The Impact of Airline Differentiation on Marginal Cost Pricing at UK Airports, *Transportation Research* A 55, 72-88.

40. Zhao, Q., Y. Y. Choo, and T. H. Oum (2014), The Effect of Governance Forms on North American Airport Efficiency: A Comparative Analysis of Airport Authority vs. Government Branch, *Transportation Research Forum*, 53, 93-110.

Appendix I

Acronyms

BAA	British Airports Authority (now Heathrow Airport Holdings Limited)	OLS	ordinary regression analysis
BYS	Bayesian	PAX	passengers
CD	Cobb-Douglas	PPP	public private partnerships
CRS	constant returns to scale	RTS	returns to scale
DEA	data envelopment analysis	SFA	stochastic frontier analysis
DRS	decreasing returns to scale	SGM	Symmetric Generalized McFadden
ECU	economies of capital utilization	SR	short run
EU	European Union	TCE	transaction cost economics
IRS	increasing returns to scale	TFP	total factor productivity
K, L	capital, labor	TL	translog
LCC	Low-cost carrier	UK	United Kingdom
LR	long run	US	United States
N/A	Not applicable	VFP	variable factor productivity
NA	North America		

Data and Transformations

Variable	Explanation	Transformation
q	Output measure	Log-demeaned
k	Capital measure	Log-demeaned
l	Personnel price	Log-demeaned
e	Airport operations price	Log-demeaned
k	Capital variable	Log-demeaned
Share of international departures		Demeaned
Share of freight		Demeaned
Parking	% of Parking in Non-Aeronautical Revenues	Demeaned
Retail	% of Retail in Non-Aeronautical Revenues	Demeaned
Hub	Large hub dummy	
Local	Local ownership dummy	
MAP	Multi-airport dummy	
MAPJO	Multi-airport Joint ownership dummy	
t	Time trend	

Appendix II

Airports in the Sample (2008 Hub Status)

Large Hubs

Airport	Airport Code	MAP	MAPalt	MAPJO	Local	Airport	Airport Code	MAP	MAPalt	MAPJO	Local
Hartsfield - Jackson Atlanta Int'l	ATL*	0	0	0	1	Los Angeles Int'l	LAX	1	1	0	1
General Edward Lawrence Logan Int'l	BOS	0	0	0	1	La Guardia	LGA	1	1	1	1
Baltimore/Washington Int'l	BWI	0	1	0	0	Orlando Int'l	MCO*	0	0	0	1
Charlotte/Douglas Int'l	CLT	0	0	0	1	Chicago Midway Int'l	MDW	1	1	1	1
Ronald Reagan Washington National	DCA	1	1	1	1	Miami Int'l	MIA	1	1	0	0
Denver Int'l	DEN*	0	0	0	1	Minneapolis-St Paul Int'l	MSP	0	0	0	1
Dallas/Fort Worth Int'l	DFW*	1	1	0	1	Chicago O'hare Int'l	ORD*	1	1	1	1
Detroit Metropolitan Wayne County	DTW*	0	0	0	0	Philadelphia Int'l	PHL	0	0	0	1
Newark Liberty Int'l	EWR	1	1	1	1	Phoenix Sky Harbor Int'l	PHX	0	0	0	1
Fort Lauderdale/Hollywood Int'l	FLL	1	1	0	0	San Diego Int'l	SAN	0	1	0	1
Washington Dulles Int'l	IAD	1	1	1	1	Seattle-Tacoma Int'l	SEA	0	0	0	1
John F Kennedy Int'l	JFK*	1	1	1	1	Salt Lake City Int'l	SLC	0	0	0	1
Mc Carran Int'l	LAS*	0	0	0	0	Tampa Int'l	TPA	0	0	0	1
Medium Hubs											
Albuquerque Int'l Sunport	ABQ	0	0	0	1	Memphis Int'l	MEM	0	0	0	1
Austin-Bergstrom Int'l	AUS	0	1	0	1	General Mitchell Int'l	MKE	0	0	0	0
Bradley Int'l	BDL	0	0	0	0	Louis Armstrong New Orleans Int'l	MSY	0	0	0	1
Nashville Int'l	BNA	0	0	0	1	Palm Beach Int'l	PBI	1	1	0	0
Bob Hope	BUR	1	1	0	1	Portland Int'l	PDX	0	0	0	1
Cleveland-Hopkins Int'l	CLE	0	0	0	1	Pittsburgh Int'l	PIT*	0	0	0	1
Port Columbus Int'l	CMH	0	0	0	1	Raleigh-Durham Int'l	RDU	0	0	0	1
Cincinnati/Northern Kentucky	CVG	0	1	0	1	Southwest Florida Int'l	RSW	0	0	0	1
Dallas Love Field	DAL	1	1	0	1	San Antonio Int'l	SAT	0	1	0	1
Indianapolis Int'l	IND	0	1	0	1	Sacramento Int'l	SMF	0	0	0	0
Jacksonville Int'l	JAX	0	0	0	1	John Wayne Airport-Orange County	SNA	1	1	0	0
Kansas City Int'l	MCI	0	0	0	1	Lambert-St Louis Int'l	STL*	0	0	0	1

Note: * Indicates that the Top10ENSR = 1

Appendix III

The following table includes three sections: The Multiple Airport section presents estimation results when we replace MAP with its alternative definition (MAPalt) and while keeping the rest of the variables the same as our benchmark model (Table 5). The frontier parameters for the benchmark model and this model are similar, at least in statistical sense. That is, the parameters generally differ little relative to their standard errors. However, there is a sign change in the MAP variable. As in our benchmark scenario, this change has a small effect on the sample median average variable cost due to inefficiency (1.55% change).

Hub section presents estimation results when we replace Hub with its alternative definition and keep the rest of the variables same as our benchmark model. In general, the frontier parameters for this model and the benchmark model are similar as are the parameter estimates for the efficiency term .

Number of Runways section presents estimation results when we include the number of runways as an additional regressor and keep rest of the variables same as our benchmark model. We again find that this model and the benchmark model produce frontier parameter estimates and estimates for the efficiency term that are generally similar. Note that, although the coefficient for number of runways is significant, the likelihood ratio test and Bayesian Information Criteria support the restricted model without this term. In our benchmark model the MAP and MAPJO coefficients are significant at 10% level. However, they become insignificant when we include number of runways. This outcome, however, is not contradicting with our general findings that governance does not have much effect on efficiency.

We conclude that the parameter estimates and the median of efficiency estimates in these models are similar to those in the benchmark model indicating that the benchmark model is robust to alternative models and variables.

Other Stochastic Frontier Estimation Results

	Multiple Airport			Hub			Number of Runways		
Parameter	**Estimate**	**Std Err**	**Pr>|t|**	**Estimate**	**Std Err**	**Pr>|t|**	**Estimate**	**Std Err**	**Pr>|t|**
Constant	17.7807	0.0309	0.0000	17.7660	0.0297	0.0000	17.9417	0.0265	0.0000
q **(Departures)**	0.4551	0.0796	0.0000	0.4693	0.0665	0.0000	0.4509	0.0871	0.0000
q^2	0.1008	0.1856	0.5872	0.0822	0.1943	0.6724	0.0523	0.2004	0.7943
k **(ENSR)**	0.0075	0.0742	0.9194	0.0090	0.0717	0.8997	0.1604	0.0616	0.0092
k^2	-0.7810	0.3025	0.0098	-0.8065	0.2666	0.0025	-0.7021	0.3118	0.0243
$q*k$	-0.3573	0.1070	0.0008	-0.3376	0.0928	0.0003	-0.3643	0.1053	0.0005
l **(Personnel Price)**	0.3852	0.0047	0.0000	0.3853	0.0047	0.0000	0.3853	0.0047	0.0000
e **(Operations Price)**	0.2196	0.0053	0.0000	0.2195	0.0053	0.0000	0.2196	0.0053	0.0000
l^2	-0.1290	0.0615	0.0360	-0.1217	0.0609	0.0459	-0.1221	0.0611	0.0456
e^2	-0.6912	0.1145	0.0000	-0.6878	0.1143	0.0000	-0.6878	0.1143	0.0000
$l*e$	0.3641	0.0666	0.0000	0.3590	0.0662	0.0000	0.3592	0.0663	0.0000
$l*q$	-0.0567	0.0269	0.0351	-0.0549	0.0269	0.0411	-0.0551	0.0269	0.0405
$e*q$	0.0110	0.0310	0.7216	0.0102	0.0309	0.7416	0.0103	0.0309	0.7402
$l*k$	0.0636	0.0094	0.0000	0.0640	0.0093	0.0000	0.0639	0.0093	0.0000
$e*k$	-0.0148	0.0106	0.1617	-0.0149	0.0106	0.1596	-0.0150	0.0106	0.1569
$q*Local$	-0.3445	0.0610	0.0000	-0.3461	0.0555	0.0000	-0.3409	0.0618	0.0000
$k*q*Top10ENSR$	0.4881	0.2245	0.0297	0.4068	0.2178	0.0618	0.4226	0.2353	0.0725
q*Hub	0.0624	0.0662	0.3461	0.0538	0.0544	0.3231	0.0636	0.0683	0.3516
Share of int'l departures	0.6966	0.2252	0.0020	0.7957	0.2180	0.0003	0.7797	0.2234	0.0005
Share of freight	0.0546	0.1112	0.6234	0.0326	0.1112	0.7691	0.0524	0.1150	0.6487
Parking (% in Revenue)	-0.2377	0.1064	0.0255	-0.2584	0.0937	0.0058	-0.2435	0.1048	0.0202
Retail (% in Revenue)	0.2080	0.0940	0.0270	0.1942	0.0942	0.0393	0.1812	0.0910	0.0466
# of Runways	-	-	-	-	-	-	-0.0482	0.0095	0.0000
Year Dummy Variables									
D1998	0.0154	0.0287	0.5921	0.0243	0.0207	0.2415	0.0230	0.0212	0.2775
D1999	0.0822	0.0214	0.0001	0.0917	0.0196	0.0000	0.0856	0.0195	0.0000
D2000	0.0855	0.0204	0.0000	0.0941	0.0190	0.0000	0.0873	0.0189	0.0000
D2001	0.1133	0.0210	0.0000	0.1231	0.0193	0.0000	0.1189	0.0183	0.0000
D2002	0.1499	0.0262	0.0000	0.1643	0.0243	0.0000	0.1580	0.0234	0.0000
D2003	0.1980	0.0250	0.0000	0.2134	0.0232	0.0000	0.2047	0.0233	0.0000
D2004	0.1682	0.0242	0.0000	0.1893	0.0227	0.0000	0.1795	0.0228	0.0000
D2005	0.1701	0.0255	0.0000	0.1879	0.0243	0.0000	0.1802	0.0249	0.0000
D2006	0.1563	0.0241	0.0000	0.1719	0.0235	0.0000	0.1679	0.0243	0.0000
D2007	0.1843	0.0247	0.0000	0.1977	0.0237	0.0000	0.1925	0.0244	0.0000
D2008	0.1880	0.0231	0.0000	0.2013	0.0226	0.0000	0.1966	0.0237	0.0000
$\sigma^2(u)$									
Constant	-1.3586	0.0242	0.0000	-1.1402	0.0834	0.0000	-1.1619	0.0999	0.0000
Hub	-0.7727	0.1302	0.0000	-0.7194	0.1358	0.0000	-0.7433	0.1392	0.0000
Local	0.4757	0.0546	0.0000	0.5570	0.0289	0.0000	0.4696	0.0553	0.0000
MAP (Multiple airport)	0.2039	0.0998	0.0410	-0.0934	0.0381	0.0143	-0.1188	0.1578	0.4514
MAPJO (Jointly operated)	0.0575	0.2134	0.7877	0.1949	0.2045	0.3406	0.2704	0.2365	0.2530
k	0.1753	0.1039	0.0915	0.2065	0.0682	0.0024	0.1968	0.0497	0.0001
k^2	0.1657	0.1547	0.2842	0.2593	0.0437	0.0000	0.2466	0.0366	0.0000
t **(Trend)**	-0.4659	0.0087	0.0000	-0.5380	0.0118	0.0000	-0.5118	0.0116	0.0000
t^2	0.0257	0.0007	0.0000	0.0297	0.0006	0.0000	0.0285	0.0006	0.0000
$\sigma^2(v)$									
Constant	-10.2777	0.0242	0.0000	-10.2042	0.0826	0.0000	-10.2930	0.0949	0.0000
Log-likelihood		1406.9			1404.3			1406.4	
Median Efficiency		87.7			87.7			87.9	
# of Violations		5/649			2/649			2/649	