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Demand Uncertainty and Cost Efficiency:

An empirical study of airline industry

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***Abstract*—Demand uncertainty is the crucial concerns of airline production planning. The airlines regularly fly their airplane below full capacity because fare and capacity need to be set before it operates. During this period, actual demand is more likely to deviate from its forecast. Unsold tickets would lead to lower operating revenue and create unnecessary costs of operation. This study aims at investigating the empirical impact of firm-level volatility on production cost and efficiency. The purposes are to examine the relationship between demand uncertainty and operating cost of an airline, and empirically measure the airline cost competitiveness when taking demand volatility into consideration.**

***Keywords*—demand uncertainty, airline's cost, cost efficiency**

I. Introduction

There have been many studies suggesting that airline industry performance is significantly correlated with the overall economic conditions. Over the past decades, several airlines have encountered operating difficulty and resulting poor financial results. One potential source could be from a large increase in fluctuations at firm-level as found in previous studies [1-4]. In literature, there have been at least two sources of market fluctuations that firms have to face with [5]. One is an uncertainty from the evolution of possible demand and overall economy, which it is typically exogenous to the industry. The other is market volatility that emerges endogenously from the strategic decisions of firms due to asymmetric information about the strategic rationales underlying competitive behaviors such as cost structure and financial constraints of the rivals. Individual firms need to handle the fluctuation/uncertainty not only from market situation, but also from other competitors' reactions.

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Economic cycle, industrial shocks, and competitive issues have attracted significant attention for airline manager to draw an effective plan to handle. Demand fluctuation or uncertainty has considerable influence on firm's operations since market decisions need to be made prior to actual demand has been realized. This is key important area for airline industry, because the possible unsold tickets would lead to lower operating revenue. Not only airfare, aircraft planning decisions also need to be made in advance with long capacity installation lead times and highly volatile demand. The deviation of actual demand from forecast would possibly create unnecessary cost of operations, which in turn affect a significant portion of future revenue. Not only would it lower revenue, implicit costs associated with it would result in.

While a fairly body of literature in this area has been devoted for theoretical work, as far as researcher is aware, only few studies have empirically examined the effect of demand uncertainty in transportation industry. Among the others, Rodriguez-Alvarez [6] examined cost function of ports in Spain and found that demand uncertainty has a significant effect on costs. Since there is research gap in this area, this study aims to investigate the relationship between demand uncertainty and operating cost of an airline and empirically measure the airline cost competitiveness when taking demand fluctuation into consideration. The study is novel in literature from which it proposes the empirical framework to measure firm-level fluctuations from demand uncertainty on transportation industry, particularly on airline industry.

The study utilizes the major US airlines as a case study. According to statistical report of Bureau of Transportation Statistics, the U.S. Department of Transportation, in 2006 these airlines shared over 60% of total traffic and 50% of domestic traffic in term of available seat-miles (ASMs). In addition, the US aviation market is regarded as one of the most mature and liberal market in the world. It is thus expected that the results from this study's analyses can be used to represent the industrial insight and provide important implications for other markets.

The remaining sections are laid out as follows. Section II proposes empirical framework to measure firm-level demand uncertainty. Section III presents econometric models for airline's cost function estimation. Section IV discusses empirical results on airline's cost efficiency associated with demand volatility. Concluding remarks are expressed in the last section.

II. Empirical Measure of Demand Uncertainty

A. Data Description

In this study, we focus on cost function estimation of major US airlines. The sample airlines are Alaska (Alaska), America West (AWA), American (AA), Continental (CO), Delta (DL), Northwest (NW), United (UA), and US Air (US). The data are on a quarterly basis, ranged from the first quarter of 1996 to the fourth quarter of 2009. Note that American West and US Air have fully merged their operations since the fourth quarter of 2006 and then the data have been appeared as only US Air. This yields an unbalanced panel data set with total 431 observations after constructing and transforming the data. The main sources of data are mainly from Bureau of Transportation Statistics supplemented with data from other sources, if necessary, for example, airline's website and private-related agencies.

B. Demand Uncertainty Measure

We first construct the empirical measure for firm-level market fluctuation or demand uncertainty. Since market demand cannot be observed, we use airline's actual sales on flights as measured by revenue passenger miles (RPMs) and estimate the standard deviation of the unpredictable part of log-change in sales as a proxy for market uncertainty followed Rodriguez-Alvarez et al. [6], McConnell and Perez-Quiros [7], Blanchard and Simon [8], Cogley and Sargent [9], and Campbell [10]. The use of standard deviation is widely found in a variety of literature and commonly taken as an empirical measure of demand uncertainty in economics , such as Comin and Mulani [4], Rodriguez-Alvarez et al. [6], and Davis and Kahn [11]. The estimation procedures are carried out in two stages. First, we estimate the forecasted demand by assuming that demand of each airline follows a simple AR(1) process and the demand equation to be forecasted is defined as follows:

$$\ln Demand_t = \alpha_0 + \alpha_1 \ln Demand_{t-1} + \sum_i \delta_i Carrier_i + \sum_i \gamma_i Quarter_i + \varepsilon_t , \quad (1)$$

where demand is measured by airline's sales; $Demand_{t-1}$ is the demand in previous period; $Carrier_i$ are dummy variables for firms' effects; and $Quarter_i$ are dummy variables for quarter. In second stage, we estimate the variance function by using the errors obtained from (1) and employing the methodology proposed by Harvey [12] in that the model specification is $Var(\varepsilon) = \exp(z\beta)$, where z's are usually, but not necessarily, the same variables in the (mean) demand function. Thus, we regress the log of squared errors on all explanatory variables appeared in (1). This allows us to estimate standard deviation of demand, which is a measure of market fluctuation in our study.

Regression results of forecasted demand and demand variance are reported in Table I. Demand variation measure will be taken to airline's cost function models, which will be specified in next sections.

TABLE I. REGRESSION RESULTS ON DEMAND UNCERTAINTY MEASURE

Variables	Model 1: Forecasted demand		Model 2: Demand variance	
	Coef.	Std.	Coef.	Std.
Lagged demand	0.7495	0.0315	0.0376	0.0179
Alaska	0.5293	0.0735	-0.0783	0.0417
AWA	0.0816	0.0315	-0.0100	0.0179
CO	0.3680	0.0541	-0.0551	0.0307
DL	0.4799	0.0679	-0.0744	0.0386
NW	0.3788	0.0571	-0.0576	0.0324
UA	0.5077	0.0716	-0.0795	0.0406
US	0.2761	0.0453	-0.0391	0.0257
Constant	5.6240	0.6913	-0.8224	0.3925
Observations		*431*		*431*
Adjust R-squared		*0.9647*		*0.1133*
Prob > F		*0.0000*		*0.0000*

III. Econometric Models for Airline's Cost

A. Empirical Models

Then, we estimates a variable cost function by taking the impact of demand uncertainty into account. Since capital input is always in short-run disequilibrium, it is treated as a quasi-fixed input. Following Caves et al. [13] and Gillen et al. [14] a translog variable cost function is specified as follows:

$$\ln VC = f\left(Y, \mathbf{W}_i, uK, Z, SD, Carrier_i, Year_t\right), \quad (2)$$

where VC is the cost of variable inputs; Y is the aggregate output index; $\boldsymbol{W_i}$ is a vector of input prices (labor, fuel, and purchased services and materials inputs); K is capital stock which is treated as fixed in the short run; u is utilization rate of capital stock (measured as weight load factor); Z is average stage length of an airline during the quarter; SD is estimated standard deviation representing demand variation of an airline; and $Carrier_i$ *and* $Year_i$ are dummy variables used to capture the effect of firm size and shifts in technological efficiency over time.

To improve the efficiency of estimation, the study introduced cost share equation and shadow value of capital stock into the equation system. By appling Shephard's lemma to the variable cost function (2), the variable input cost share equations can be obtained as $S_i = \partial \ln VC / \partial \ln \mathbf{W}_i$. The shadow value of capital stock (followed the methodology of [15-18]) can be derived by $\left(C_k / VC\right) = -\left(\partial \ln VC / \partial \ln(uK)\right)$, where C_k is the depreciated capital cost. It is basically the first order condition for short-run total cost minimization which endogenizes the capacity utilization. The traditional restrictions of the homogeneous of degree one in input prices were additionally imposed on the parameters of the translog cost function. The equation system of translog cost function, cost share equations, and shadow value of capital stock will be then jointly estimated by Iterated Zellner Seemingly Unrelated method by treating firm heterogeneity as a fixed effect.

B. *Variable Construction*

Airline's output, input, network, and operational attributes as formed in previous section, can be described as follows:

- Output (Y): Airline's output in this study is classified into four categories including passenger, freight, mail, and incidental services. Except the incidental services, all other outputs are measured in Revenue-Tonne-Miles (RTMs). All the airline's outputs are aggregated by using the translog multilateral index procedure proposed by Caves et al. [19] with the revenue shares as weights in the aggregation.
- Input cost (W_i): The airline's input costs are collected from labor, fuel, and purchased services and materials inputs.
- Short-term adjustment in capital stock (uK): There are two variables when constructing this variable. One is total capital input (K) as measured by an aggregate of flight equipment, and ground property and equipment (GPE). The other one is weight load factor (u), used as a proxy for capital utilization rate reflecting short-run disequilibrium [20].
- Average stage length (Z): Average stage length is the average distance flown, measured in miles, per aircraft departure. The measure is calculated by dividing total aircraft miles flown by the number of total aircraft departures performed.
- A measure of uncertain demand (SD): An empirical measure of airline's demand uncertainty is taken from the method proposed in section II.
- Shadow value share to total variable costs (C_k): This variable is approximated by the total capital cost multiplied by utilization rate.
- Other dummy variables: $Year_i$ are year dummy variables to capture time effects and technological shifts on the variable costs. $Firm_i$ are accounted for unobservable airline's operational and managerial strategies across the airlines in our sample.

C. *Cost Estimated Result*

The estimated result is reported in table II. We first estimated the cost system without an uncertainty impact as shown in model 1. Then, the estimates with an introduction of market demand fluctuation are reported in the second panel as model 2. Since the measure of demand uncertainty rises a potential endogeneity problem which would cause inconsistent estimates. To account for the possible problem, we proposed lagged differences in demand as an instrumental variable, which is $\Delta \ln Demand_{t-1} = \ln Demand_{t-1} - \ln Demand_{t-2}$, followed Rodriguez-Alvarez et al. [6]. The cost equation system was re-estimated by using Three-stage Least Square (3SLS) procedure. Due to limited space, the estimated results were summarized in the last panel as model 3.

TABLE II. AIRLINE'S COST FUNCTION ESTIMATION

Cost	Model 1: No Uncertainty		Model 2: SUR		Model 3: 3SLS	
	Coef.	Std.	Coef.	Std.	Coef.	Std.
Output (Y)	0.4082	0.0873	0.4535	0.0861	0.5255	0.0933
Fuel price	0.3790	0.0062	0.3778	0.0062	0.3755	0.0062
Labor price	0.2413	0.0065	0.2413	0.0065	0.2401	0.0065
Material price	0.3797	0.0080	0.3809	0.0080	0.3845	0.0080
Stage length	-0.5951	0.1296	-0.6603	0.1280	-0.7450	0.1384
Capital	0.3709	0.0712	0.3159	0.0709	0.2401	0.0817
Uncertainty			**0.0516**	**0.0132**	**0.1586**	**0.0390**
Observation		*431*		*431*		*431*
Adjusted R-squared		*0.9723*		*0.9706*		*0.9706*

a. All variables except firm and time dummies were in natural logarithm form and normalized at mean value.

Before turning our attention to the impacts of market volatility, we looked into the estimated parameters of key control variables. The first-order coefficients of those variables are found statistically significant and of expected sign. The coefficient of input prices indicates that, at mean value, fuel and material inputs have an identical cost share at around 38% of the total variable cost, while labor input accounts for 24%. Our recent evidence shows that fuel cost gained substantial share as compared to the estimates in [18] and [20]. This clearly reflects a rapid rise of fuel prices over the sample time period. The positive first-order coefficient for capital implies a negative shadow value of capital input [21-23]. The stage length's coefficient is statically significant with negative value, suggesting that, ceteris paribus, an airline with longer average stage length would gain cost benefit as seen from a decrease in estimated variable cost.

IV. The Effect of Demand Uncertainty on Cost Efficiency

The impact of demand volatility on the total variable cost is statistically significant. Utilizing the estimated results of airline's cost estimation, holding all the other relevant factors constant, the findings indicate that the higher level of uncertainty will cause an increase in airline's operating cost. This implies that when airlines are facing with uncertain demand, they need to use more inputs to produce the same level of travel services. As a result, there occur unnecessary costs resulted from inefficiency of resource allocation.

Since demand volatility can lead to the inefficiency of resource allocation and input utilization, we calculated input-oriented cost efficiency indices for translog cost functions with panel data so as to look into how the efficiency would change corresponding to the uncertainty level. Followed the method proposed by Atkinson and Cornwell [16], denoted the efficient input quantity as $x_i^* = a_i x_i$ and the input-oriented cost frontier as $C^*(y, w_i)$, indicating the minimum cost of producing output given input prices and technology level. The observed cost of an airline can be expressed as $C_i = C^*(y, w_i) \cdot (1/a_i)$. Given the translog cost specification, $\ln(1/a_i)$ is the distance of airline i from the cost frontier and in turn reflects the input-oriented cost efficiency. Note that since the fixed effect coefficients have also captured other unobservable factors apart from firm heterogeneity, we strictly assume that such the unobserved factors are not related to the efficiency level and constant across the estimate. The estimated results are given in table III.

TABLE III. AIRLINE'S INPUT-ORIENTED COST EFFICIENCY COMPARISON

Airlines	Average uncertainty	Without demand uncertainty	With demand uncertainty	
			SUR	3SLS
American Airlines	0.0011	1.2494	0.9739	0.8306
Alaska Airlines	0.0029	0.8452	0.7928	0.7737
America West Airlines	0.0030	0.8275	0.7661	0.7374
Continental Air Lines	0.0016	0.9598	0.9257	0.9513
Delta Air Lines	0.0006	**1.0000**	**1.0000**	**1.0000**
Northwest Airlines	0.0012	0.9235	0.8764	0.8872
United Air Lines	0.0006	1.1769	0.9739	0.8306
US Airways	0.0019	0.7560	0.6902	0.6614

a. Estimated values are normalized as the value of Delta Air Lines.

The airline's input-oriented cost efficiency indices are normalized by the value of Delta Air Lines. American Airlines, United Air Lines, and Delta Air Lines were carriers in the top score of efficient operation. It is evident that without taking demand uncertainty measure into account, the efficiency indices are higher. This is consistent with intuition. The presence of demand uncertainty requires airline to use more input than necessary to produce to same level of output, which in turn causes higher costs and less efficiency. The airlines with more market variation would thus have lower efficiency indices, which were Alaska Airlines and America West Airlines in this study. One may question this is unfair to these airlines because firm-level market fluctuation may not be the same. In fact, they may have well-planned management. As such, demand uncertainty could probably overestimate inefficiency of the airlines'

To consider airline with different level of demand uncertainty, we calculated the variable cost changes associated with level of demand uncertainty. Given other factors being constant, if the airlines had demand uncertainty at the lowest possible level, we asked how much operating cost would be increased as a result of market volatility compared with based airline. We use the estimated coefficient of demand uncertainty in cost function and compute Variance-adjusted Cost Efficiency (VCE_{SD}) indices, with the following formula: $VCE_{SD} = (SD_{\min} / SD_i)^{b_{SD}}$.

Table IV presents the variance-adjusted cost efficiency indices, normalized by the value of Delta Air Lines. The estimated values of airline's cost efficiency are virtually higher when adjusting for variance variation. SUR and 3SLS yield very close values among the airlines. This confirms the claim that the presence of demand uncertainty would overestimate airline's inefficiency or underestimate actual efficiency levels.

TABLE IV. AIRLINE'S VARIANCE-ADJUSTED COST EFFICIENCY

Airlines	Average uncertainty	SUR ($I_{b_{SD}^{SUR}}$=0.0516)	3SLS ($I_{b_{SD}^{3SLS}}$=0.1586)
American Airlines	0.00106	0.9725	0.9179
Alaska Airlines	0.00292	0.9228	0.7811
America West Airlines	0.00300	0.9215	0.7777
Continental Air Lines	0.00156	0.9532	0.8629
Delta Air Lines	0.00062	**1.0000**	**1.0000**
Northwest Airlines	0.00115	0.9683	0.9056
United Air Lines	0.00062	0.9994	0.9982
US Airways	0.00186	0.9446	0.8393

a. Estimated values are calculated by using mean value of each variable and normalized as the value of Delta Air Lines.

V. Concluding Remarks

This paper proposed a framework to measure the empirical impact of firm-level market fluctuations or demand uncertainty on airline's cost and cost efficiency. A case study of eight major airlines in the United State market was adopted to test economic hypothesis on the impact of demand changes with data from 1996 to 2009. Airline's translog cost function was estimated and used to compute the efficiency indices. The empirical findings suggest that demand uncertainty has significant impact on airline's cost. Airlines with high demand variation would have less cost efficiency. The study further questioned this is probably unfair to rank these airlines as inefficiency, since it is from market volatility, not essentially from airline's true operation. Thus, the variance-adjusted cost efficiency was re-estimated. It confirmed that different demand variation would lead to misleading justification because uncertainty in demand overestimated airline's inefficiency or under estimate actual efficiency. This study provides insight implications regarding airline's operations when facing with own-firm demand volatility. Airline manager may utilize findings to design an action plan for demand forecast and cost management. Industrial policy makers can observe the empirical relation which helps propose an appropriate policy in accordance with current market situation.

References

[1] J.Y. Campbell, M. Lettau, B. Malkiel and Y. Xu, "Have individual stocks become more volatile? an empirical exploration of idiosyncratic risk," Journal of Finance, Vol 56 (1), pp. 1-43, 2001.

[2] T. Chaney, X. Gabaix and T. Philippon, "Firm Volatility," MIT, mimeo, 2002.

[3] D. Comin, "An uncertainty-driven theory of the productivity slowdown," Harvard University, unpublished thesis, 2000.

[4] D. Comin and S. Mulani, "Diverging trends in aggregate and firm volatility," Review of Economics and Statistics, Vol 88, pp. 374-383, 2006.

[5] D. Besanko, L.X. Doraszelski and M. Satterthwaite, "On the role of demand and strategic uncertainty in capacity investment and disinvestment dynamics," International Journal of Industrial Organization, Vol 28 (4), pp. 383-389, 2010.

[6] A. Rodriguez-Alvarez, B. Tovar and A. Wall, "The effect of demand uncertainty on port terminal costs," Journal of Transport Economics and Policy, Vol 45 (2), pp. 303-328, 2011.

[7] M. McConnell and G. Perez-Quiros, "Output Fluctuations in the United States: What has changed since the early 1980's," American Economic Review, Vol 90 (5), pp. 1464-1476, 2000.

[8] O. Blanchard and J. Simon, "The long and large decline in U.S. output volatility," Brookings Paper on Economic Activity, Vol 1, pp. 135-164, 2001.

[9] T. Cogley and T.J. Sargent, "Drifts and volatilities: monetary policies and outcomes in the post WWII US," Review of Economic Dynamics, Vol 8 (2), pp. 262-302, 2005.

[10] S.D Campbell, "Macroeconomic volatility, predictability, and uncertainty in the Great Moderation: Evidence from the survey of professional forecasters," Journal of Business & Economic Statistics, Vol 25, pp. 191-200, 2007.

[11] S. Davis and J. Kahn, "Interpreting the Great Moderation: Changes in the volatility of economic activity at the macro and micro levels," Journal of Economic Perspectives, Vol 22, pp. 155-180, 2008.

[12] A.C. Harvey, "Estimating regression models with multiplicative heteroschedasticity," Econometrica, Vol 44 (3), pp. 461-465, 1976.

[13] D.W. Caves, L.R. Christiansen and M.W. Trethwa, "Economies of destiny versus economies of scale: why trunk and local service airline costs differ," RAND Journal of Economics, Vol. 15 (4), pp. 471-489, 1984.

[14] D.W. Gillen, T.H. Oum and M.W. Tretheway, "Airline cost structure and policy implications," Journal of Transport Economics and Policy, Vol. 24 (2), pp. 9-34, 1990.

[15] T.H. Oum and Y. Zhang, "Utilization of quasi-fixed inputs and estimation of Cost functions," Journal of Transport Economics and Policy, Vol. 25 (2), pp. 121–134, 1991.

[16] S.E. Atkinson and C. Cornwell, "Estimation of output and input technical efficiency using a flexible functional form and panel data," International Economic Review, Vol 35, pp. 245-56, 1994.

[17] T.H. Oum and C. Yu, "A productivity comparison of the world's major airlines," Journal of Air Transport Management, Vol. 2, pp. 181-195, 1995.

[18] W. Homsombat, X. Fu and A. Sumalee, "Policy implications of airline performance indicators," Transportation Research Record: Journal of the Transportation Research Board 2177, pp. 41-48, 2010.

[19] D.W. Caves, L.R. Christensen and W.E. Diewert, "Multilateral comparisons of output, input, and productivity using superlative index numbers," The Economic Journal, Vol. 92 (365), pp. 73-86, 1982.

[20] T.H. Oum and C. Yu, "Cost Competitiveness of the World's Major Airlines: An International Comparison," Transportation Research A. Vol. 32 (6), pp. 407-422, 1998.

[21] D.W. Gillen, T.H. Oum and M.W. Tretheway, "Airline Cost and Performance: Implications for Public and Industry Policies," Centre for Transportation Studies, University of British Columbia, Vancouver, Canada, 1985.

[22] D. W. Caves, L.R. Christensen, M.W. Tretheway, M. W. and R.J. Windle, "An assessment of the efficiency effects of U.S. airline deregulation via an international comparison". In "Public Regulation: New Perspectives on Institutions and Policies", Ed. E.E. Bailey, pp. 285-320. MIT Press, Cambridge, MA, 1987.

[23] R.J. Windle, "The World's Airlines: A Cost and Productivity Comparison," Journal of Transport Economics and Policy, Vol. 25 (1), pp. 31–49, 1991.