Demand Uncertainty and Capacity Utilization in Airlines

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International Industrial Organization Conference
March, 2012

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Motivation

- Sellers decide production before demand is realized and are likely to have unsold inventories.
- In 2009, 19.8% of US domestic flights' capacity remained empty.
- Dana and Orlov (2009) estimate that for the U.S. airline industry, a 6.7% increase in capacity utilization translates into a $2.7 billion in cost savings each year.
- Demand uncertainty. Airlines can simply match capacity with demand.

Contribution

- Pool cross-section and time-series flight-level demand realizations data in a panel GARCH.
  - Controls for time-invariant characteristics.
  - Efficiency gains in the estimation of the conditional variance.
- Present a simple theory to motivate the link between demand uncertainty and capacity utilization.
- Consistent with the theory, we find that higher demand uncertainty decreases capacity utilization.

Price Schedule

- Competitive model.
- Demand states are given by: $h = \{0,1,2,\ldots,H\}$
- With associated probabilities: $\{\rho_0, \rho_1, \ldots, \rho_H\}$
- Number of consumers buying at state h, $DEMAND_h$
- Where $DEMAND_{h+1} \geq DEMAND_h$.
- Probability that at least $DEMAND_h$ consumers buy tickets is: $\sum_{\kappa=h}^{H} \rho_\kappa$
- As in Prescott (1975) and Dana (1999), there is a unit cost of capacity λ.
- Prices are given by: $p_\omega = \dfrac{\lambda}{\sum_{h=\omega}^{H} \rho_h}$

Distribution of Demand Realizations

- Consumers have reservation values uniformly distributed $[0,\theta]$
- The demand for different batches is given by:

$$DEMAND_{\omega} - DEMAND_{\omega-1} = \left(1 - \frac{p_{\omega}}{\theta}\right)$$

- The realized aggregate demand at state h is:

$$DEMAND_{h} = \sum_{\omega=1}^{h}\left(1 - \frac{p_{\omega}}{\theta}\right)$$

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- For the price schedule let $h = \{0,1,2,\ldots,20\}$
- Let $\lambda = 1$ and $\theta = 10$.

Table 1: Demand Uncertainty and Mean Demand Realizations.

h	Std. Dev. of h	Std. Dev. of $DEMAND_h$	Mean of $DEMAND_h$
$\{0,\ldots,20\}$	5.774	4.305	8.662
$\{1,\ldots,19\}$	5.196	3.901	8.858
$\{2,\ldots,18\}$	4.619	3.568	8.996
$\{3,\ldots,17\}$	4.041	3.214	9.111
$\{4,\ldots,16\}$	3.464	2.826	9.194
$\{5,\ldots,15\}$	2.887	2.414	9.256

Price schedule derived with $h = \{0,1,2,\ldots,20\}$.

- Higher demand volatility is associated with lower average demand realizations

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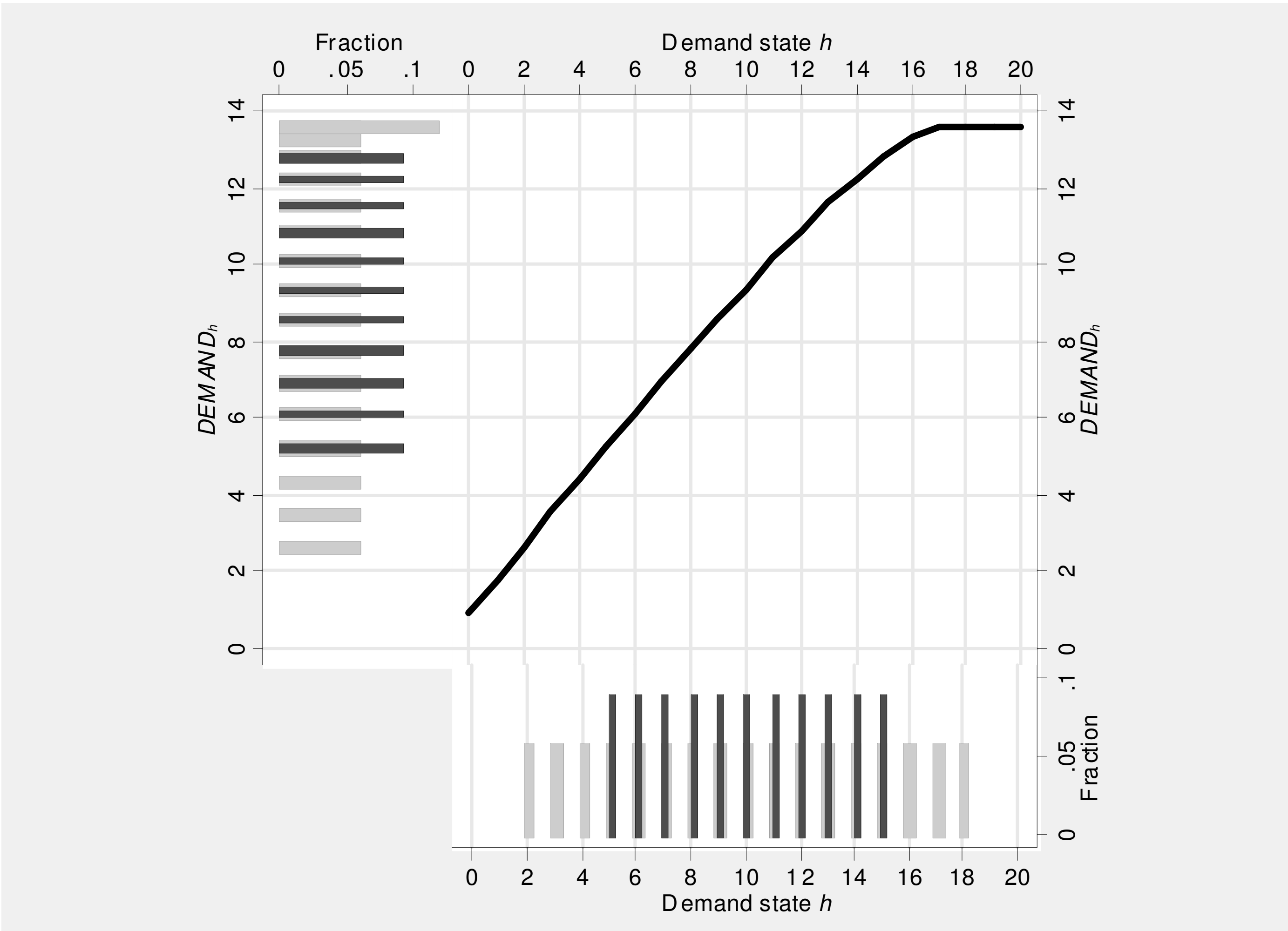
Figure 1. Demand States *h* and Demand Realizations *DEMAND*$_h$



Data

- Collected demand realizations from Expedia.com at 1, 8, and 15 days to departure.
- For 126 days between June 2 and October 6, 2009.
- Each cross-sectional unit is a non-stop one-way flight-number (e.g., American Airlines Flight 637 from Miami, FL to New Orleans, LA) that is offered everyday with the same aircraft size.
- Alaska, American, Delta, United and US Airways.

Empirical Model

$$DEMAND_{it} = \sum_{k=1}^{K} \alpha_k DEMAND_{i,t-k} + \mathbf{x}_{it}\beta + \mu_i + \varepsilon_{it},$$

- Demand uncertainty is captured by the conditional volatility

$$\sigma_{it}^2 = \phi_i + \gamma\sigma_{i,t-1}^2 + \delta\varepsilon_{i,t-1}^2$$

- Because capacity utilization is constrained to be less than 100%, the disturbance term has a truncated normal distribution. We apply Wooldridge's (1999) quasi-conditional maximum likelihood (QCML):

$$\mathcal{L} = -\frac{1}{2} NT \ln(2\pi) - \frac{1}{2}\sum_{t=1}^{T} \ln|\mathbf{\Omega}_t| - \frac{1}{2}\sum_{t=1}^{T}[(DEMAND_t - \mathbf{Z}_t\boldsymbol{\theta} - \boldsymbol{\mu})' \times \mathbf{\Omega}_t (DEMAND_t - \mathbf{Z}_t\boldsymbol{\theta} - \boldsymbol{\mu})].$$

Estimation Results

Table 4: Autocorrelation Diagnostics.

Lag	Partial Correlation					
	Residuals			Squared Residuals		
	1 Day	8 Days	15 Days	1 Day	8 Days	15 Days
1	-0.01	0.00	-0.02	0.25 ***	0.23 ***	0.22 ***
2	0.01	0.01	-0.01	0.28 ***	0.25 ***	0.19 ***
3	0.02	0.02	0.03	0.23 ***	0.17 **	0.18 **
4	0.02	0.03	0.03	0.18	0.19 ***	0.15 ***
5	0.01	0.01	0.01	0.19 ***	0.19 ***	0.18 ***
6	-0.02	-0.03	-0.02	0.21 ***	0.21 ***	0.23 ***
7	-0.04 *	-0.06 *	-0.07 *	0.20 ***	0.22 ***	0.23 ***
Q(7)	7.14	13.17	19.83	832.28 ***	737.99 ***	657.98 ***

* denotes statistical significance at the 10% level.
** denotes statistical significance at the 5% level.
*** denotes statistical significance at the 1% level.

Table 6: Panel GARCH Estimation Results.

	1 Day	8 Days	15 Days
Mean Equation:			
Intercept	0.09	0.08 ***	0.07 ***
	(0.02)	(0.02)	(0.02)
$DEMAND_{i,t-1}$	0.39 ***	0.32 ***	0.30 ***
	(0.03)	(0.03)	(0.02)
$DEMAND_{i,t-2}$	-0.06	-0.03	-0.01
	(0.03)	(0.03)	(0.03)
$DEMAND_{i,t-3}$	0.08 **	0.05 **	0.05 *
	(0.04)	(0.03)	(0.02)
$DEMAND_{i,t-4}$	0.05	0.06 *	0.001
	(0.03)	(0.03)	(0.02)
$DEMAND_{i,t-5}$	0.12 ***	0.08 **	0.08 **
	(0.03)	(0.034)	(0.03)
$DEMAND_{i,t-6}$	0.09 **	0.09 **	0.13 ***
	(0.03)	(0.03)	(0.03)
$DEMAND_{i,t-7}$	0.27 ***	0.31 ***	0.32 ***
	(0.03)	(0.03)	(0.03)
Variance Equation:			
$\sigma^2_{i,t-1}$	0.60 ***	0.73 ***	0.42 ***
	(0.06)	(0.03)	(0.11)
$\varepsilon^2_{i,t-1}$	0.93 ***	0.46 **	0.82 **
	(0.11)	(0.06)	(0.18)
Covariance Equation:			
$\sigma_{ij,t-1}$	0.54 ***	0.83 ***	0.47 ***
	(0.02)	(0.02)	(0.02)
$\varepsilon_{i,t-1}\ \varepsilon_{j,t-1}$	-0.02 ***	0.02	-0.01
	(0.01)	(0.01)	(0.01)
Log-likelihood	2738.53	1772.23	1581.27

Table 7: Panel GARCH-in-Mean Estimation Results.

	1 Day	8 Days	15 Days
Mean Equation:			
Intercept	0.09 ***	0.15 ***	0.16 ***
	(0.02)	(0.04)	(0.03)
$DEMAND_{i,t-1}$	0.36 ***	0.32 ***	0.29 ***
	(0.03)	(0.03)	(0.02)
$DEMAND_{i,t-2}$	-0.07	-0.04	-0.02
	(0.04)	(0.03)	(0.03)
$DEMAND_{i,t-3}$	0.06 **	0.04 **	0.04 *
	(0.03)	(0.03)	(0.02)
$DEMAND_{i,t-4}$	0.03	0.05 *	-0.001
	(0.03)	(0.03)	(0.02)
$DEMAND_{i,t-5}$	0.10 ***	0.07 **	0.07 **
	(0.03)	(0.03)	(0.03)
$DEMAND_{i,t-6}$	0.07 **	0.10 **	0.13 ***
	(0.03)	(0.03)	(0.03)
$DEMAND_{i,t-7}$	0.25 ***	0.31 ***	0.31 ***
	(0.03)	(0.03)	(0.03)
σ_{it}	-0.21 ***	-0.10 ***	-0.14 **
	(0.04)	(0.04)	(0.04)
<u>*Variance Equation:*</u>			
$\sigma^2_{i,t-1}$	0.58 ***	0.73 ***	0.76 ***
	(0.06)	(0.03)	(0.04)
$\varepsilon^2_{i,t-1}$	0.37 ***	0.46 **	0.82 **
	(0.04)	(0.06)	(0.18)
Covariance Equation:			
$\sigma_{ij,t-1}$	0.53 ***	0.82 ***	0.47 ***
	(0.02)	(0.02)	(0.02)
$\varepsilon_{i,t-1}\ \varepsilon_{j,t-1}$	-0.02 **	0.02	-0.01
	(0.01)	(0.01)	(0.01)
Log-likelihood	2745.60	1784.43	1592.11

Table 8: Panel GARCH-in-Mean (with Controls) Estimation Results.

	1 Day	8 Days	15 Days
Mean Equation:			
Intercept	0.09 ***	0.09 ***	0.15 ***
	(0.03)	(0.04)	(0.03)
$DEMAND_{i,t-1}$	0.39 ***	0.32 ***	0.27 ***
	(0.03)	(0.03)	(0.02)
$DEMAND_{i,t-2}$	-0.05	-0.03	-0.001
	(0.03)	(0.03)	(0.03)
$DEMAND_{i,t-3}$	0.09 ***	0.04 **	0.07 ***
	(0.03)	(0.02)	(0.02)
$DEMAND_{i,t-4}$	0.06	0.05 *	0.03
	(0.03)	(0.03)	(0.02)
$DEMAND_{i,t-5}$	0.19 ***	0.07 **	0.08 **
	(0.03)	(0.03)	(0.03)
$DEMAND_{i,t-6}$	0.08 **	0.10 *	0.10 ***
	(0.03)	(0.03)	(0.03)
$DEMAND_{i,t-7}$	0.24 ***	0.31 ***	0.26 ***
	(0.03)	(0.03)	(0.04)
σ_{it}	-0.20 ***	-0.11 **	-0.15 **
	(0.04)	(0.03)	(0.04)
TUESDAY	-0.02 **	-0.03 ***	-0.01 *
	(0.01)	(0.01)	(0.005)
WEDNESDAY	-0.02 **	-0.01	-0.01
	(0.01)	(0.01)	(0.01)
THURSDAY	-0.01	0.03 ***	0.04 ***
	(0.01)	(0.01)	(0.01)
FRIDAY	0.01 **	0.05 ***	0.06 ***
	(0.006)	(0.01)	(0.01)
WEEKEND	0.01 ***	0.03 ***	0.04 ***
	(0.005)	(0.01)	(0.01)
HOLIDAYS	0.03 **	0.05 **	0.07 **
	(0.01)	(0.03)	(0.03)
Variance Equation:			
$\sigma^2_{i,t-1}$	0.59 ***	0.73 ***	0.43 ***
	(0.06)	(0.03)	(0.11)
$\varepsilon^2_{i,t-1}$	0.37 ***	0.46 **	0.86 **
	(0.04)	(0.06)	(0.19)
Covariance Equation:			
$\sigma_{ij,t-1}$	0.58 ***	0.83 ***	0.76 ***
	(0.06)	(0.02)	(0.04)
$\varepsilon_{i,t-1}\ \varepsilon_{j,t-1}$	-0.04 ***	0.02	-0.01
	(0.01)	(0.01)	(0.01)
Log-likelihood	2801.60	1824.21	1681.96

Conclusion

- Airlines are the ideal place to examine the relationship between demand uncertainty and capacity utilization.
  - Capacity is set in advance.
  - Inventories expire at departure.
- Main empirical implication from the theoretical model:
  - Higher demand volatility is associated with lower average capacity utilization rates.
- Empirical results:
  - A unit increase in the standard deviation of unexpected demand leads to a 21 percent point decrease in capacity utilization.
  - The results are robust to systematic demand fluctuations over days of the week, holidays, as well as unobserved flight-, carrier-, and route-specific characteristics.