

# **Testing Theories of Scarcity Pricing and Price Dispersion in the Airline Industry**

**Discussion Remarks**

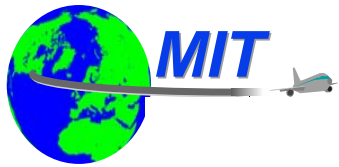
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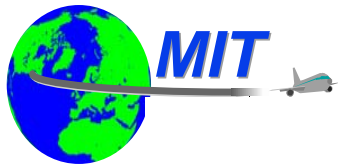
**First Annual Conference on Microeconomics**

**November 6, 2008**



# Why study airline price dispersion?

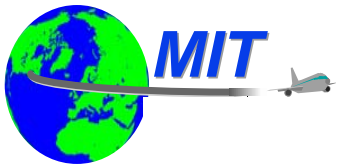
- **Airline price dispersion is substantial and ubiquitous**
  - Mean Gini coefficient in these data is 0.28:
  - May be influenced by competition on a route
- **Ongoing debate over source of this dispersion**
  - Stochastic peakload pricing in the face of uncertain demand, perishable product
  - Price discrimination across heterogeneous customers
    - Self-selective third degree price discrimination implemented by ticket restrictions correlated with demand elasticity
- **Diffusion of pricing techniques to other industries**
  - with similar heterogeneity and perishable product characteristics



# Goal of this paper

**Provide evidence distinguishing alternative theories of price dispersion in airline markets**

- **Stochastic peakload pricing**: Efficient allocation of perishable seats given uncertain demand and possible customer heterogeneity
- **Price discrimination**: (Stigler) Differential mark-ups of price over marginal (opportunity) cost, based on heterogeneity across customers in demand elasticities/willingness to pay.
  - Identified with “revenue management” model—maybe?



## Disclosure: My [Strong] Prior

- Many pricing institutions are difficult to reconcile with stochastic demand management and readily explained as segmenting demand along willingness-to-pay or elasticity dimensions
  - Advanced purchase, Saturday night stays: “Single best restriction of them all” (Northwest Airlines Internal Pricing Memo)
  - Initiatives to make discount tickets explicitly less attractive to business flyers (reduced exchange option, fee for standby, etc): reduce arbitrage opportunity across fare classes.
  - Efforts airlines put into preventing resale (unlike earlier papers in this session)— a strong suggestion that price discrimination is at work?
- But both stochastic demand management and price discrimination seem likely to play important roles (& revenue management systems pursue both)

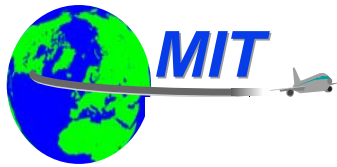


# There is more going on than realized demand for a given flight

- **Boston – Detroit: Northwest \$686** (\$457 in 2008)
  - Depart: **Mon, Oct 18, 6 am, Northwest flight 1831**
  - Return: **Wed, Oct 20, 4:58 pm, Northwest flight 332**

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- **Boston – Chicago (via Detroit): Northwest \$357** (\$411 in 2008)
  - **Depart Mon, Oct 18, 6 am,**
    - **Northwest flight 1831 BOS-DTW**
    - **Connect: Northwest flight 1237 DTW-ORD**
  - **Return Wed, Oct 20, 1:46 p.m**
    - **Northwest flight 1421 ORD-DTW**
    - **Connect: Northwest flight 332 DTW-BOS**



**There is more going on than realized demand for a given flight**

**Boston – DTW Northwest**

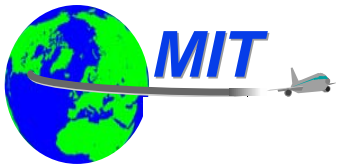
**One-way fare: \$811**

**Oct 20: BOS – DTW Northwest 371**

**RT fare : \$457**

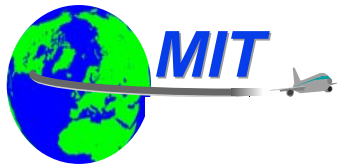
**Oct 20: BOS – DTW Northwest 371**

**Oct 22 return**



## Approach

- Careful construction of comparative static implications of models of stochastic peak load pricing**
  - Prescott model
    - Post fixed price schedule, consumers arrive over time, sell from lowest to highest P tickets as demand is realized
  - Dana (1999) model
    - Extension of model for monopoly, competition, heterogenous consumers. Maintain fixed price schedule, multiple potential demand states
  - Gale & Holmes (1992,1993)
    - Airline use limited number of discounted AP tickets to shift low-time cost consumers to offpeak flights (before they learn which flight they otherwise prefer)
- Careful construction of ticket restrictions and mapping into fares (“revenue management” model)

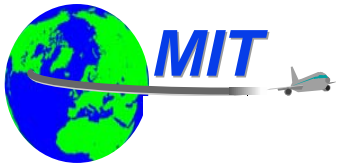


# Implementation

## Terrific new data set: CRS transactions over 2004:Q4

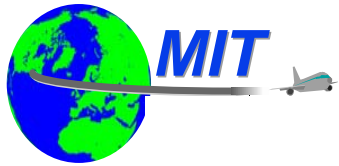
- About 1/3 of all tickets sold for domestic US flights this quarter
- Detailed data on ticket characteristics (apart from fare basis codes, which would provide ideal information on restrictions)
- Match to historical data on fare basis codes/\$ fares to attempt to infer restrictions (about 1/3 match using relatively conservative match standard)
- Compute implied load factors at a point in time from observed ticket sales
  - Scaling by mean [Sales in this channel/Total sales]– this channel may be large enough to make this a reasonable estimate, though ex post load factors aren't demand
  - Could use T100 to get better mean? (includes non OD pax)
- Potentially significant missing information: Corporate discounts (may account for some apparent anomalies)





## The Tests

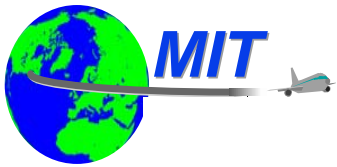
- **Compare predictions of peakload pricing models with observed (dynamic) ticket patterns**
  - Especially across flights with varying likelihood of departing full
- **Compute the predictive power of ticket restrictions for fares**
  - Assuming restrictions are motivated by “fencing” or self-selective 3<sup>rd</sup> degree price discrimination
- **Conclude that variation due to predictions of peakload pricing models is insufficient to explain degree of dispersion; additional role of restrictions suggests substantial contribution of price discrimination**



## Comments?

### A few suggestions

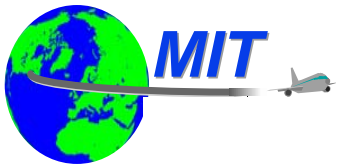
- Treatment of load factors/demand
- Corporate discounts
- Calibration of revenue



## Load Factors and Demand

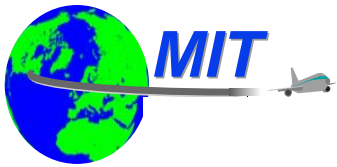
Many tests rely on identifying potential demand for a flight using realized load factors (to measure ex ante expected and/or ex post revealed demand).

- But if ticket restrictions were perfect and revenue management systems were ideal, [most?] flights would depart completely full
- Using mean within-quarter load factors for a given weekday-flight number as “expected load factor”/demand neglects information that the airlines use in setting allocations (“booking curves”)
- Could the study get some leverage from
  - Time of day/week (e.g. Friday afternoon)
  - The holiday periods they exclude?
    - We know that the two days before Thanksgiving are peak demand periods (though the nature of customers is different than for other Tuesdays and Wednesdays); maybe similar days could be identified from when Christmas falls.
    - Airlines know there is excess demand for seats on pre-Thanksgiving flights (at what price?), so no mark-up for expected perishability should be embedded in prices.



## Corporate Discounts

- These may explain why fares don't perfectly match restrictions (e.g., within 5-8%).
- More significantly, these may look like low price restricted tickets when they aren't
  - Last minute unrestricted (fully refundable) corporate shuttle fare BOS-DCA \$230 (v. \$448 unrestricted walkup fare)
- This may muddy some of the tests (esp. for 0-6 day AP tickets)
- May be able to do something with hub carriers, nonhub carriers to explore this
  - Hub carriers are the ones most likely to offer corporate discounts on routes out of their hub



## Revenue Calculations/Comparisons

- **(Some?) Stochastic peakload pricing models have predictions for expected revenue per seat—**
  - Can constructed revenue per flight (scaled for CRS coverage) be compared across flights and/or to last ticket sold on a given flight to yield insights into these models?
- **Comparison to revenue management projections:**

**Sophisticated revenue management systems are argued to increase total revenues ~5% relative to naïve reservation systems**

  - Combines effect of demand management and potential price discrimination (holding open seat for last minute high WTP passenger)
  - This may suggest that we wouldn't expect huge differences in low v. high price tickets across different flights/demand states



**This is an interesting  
and innovative paper—  
you should read it!**