Screening and Price Discrimination with Unobserved Consumer Types

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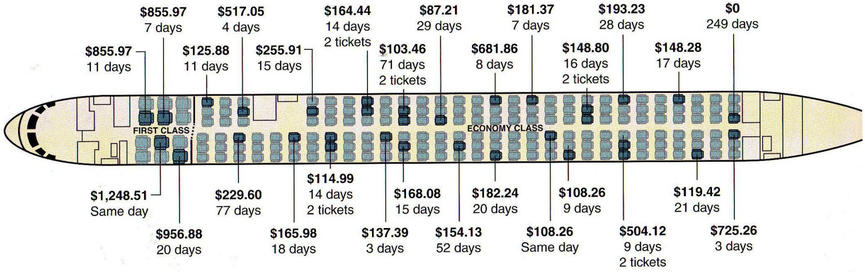
Outline

Motivation: Price dispersion in airlines

Figure: Price dispersion in airlines



- 33 passengers paid 27 different fares, United flight from Chicago to Los Angeles *(New York Times)*
- Borenstein and Rose (JPE, 1994): 36% difference.
- Gerardi and Shapiro (JPE 2009).

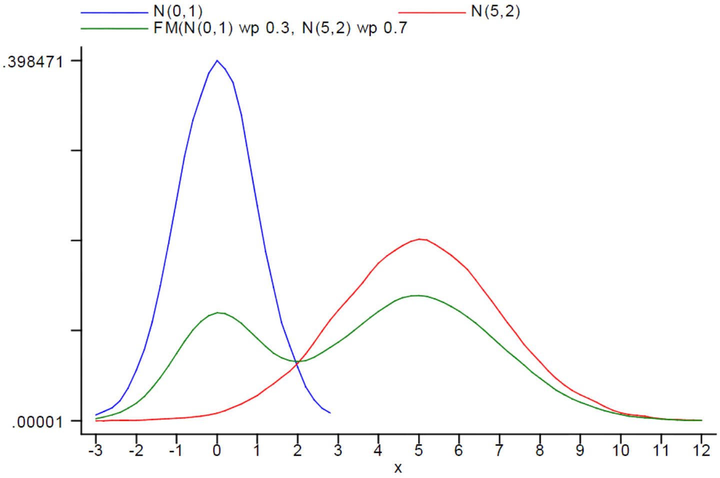
Motivation: Price discrimination in Airlines

- Carriers exploit 'fences' such as:
    - Saturday-night-stayover.
    - Advance purchase discounts.
    - Minimum- and maximum-stay.
    - Refundable tickets.
    - Frequent flier miles.
    - Blackouts.
    - Volume discounts.
    - Fare classes (e.g. coach, first class)
    - Hour-of-day purchase.
- Airlines have the most sophisticated pricing systems in the world.

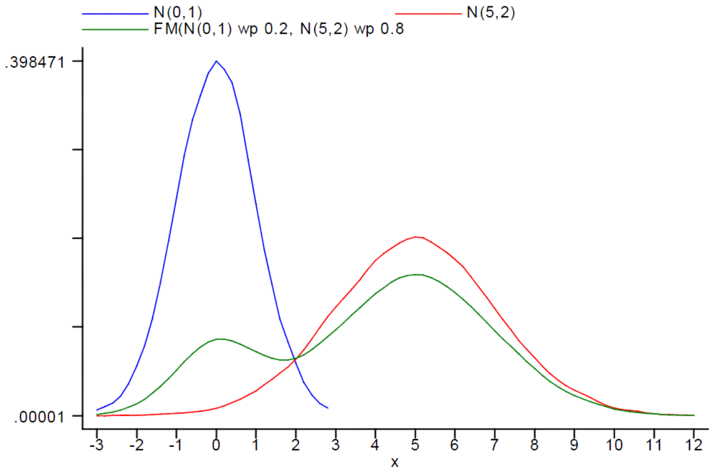
Motivation: Asymmetric Information

- Consumers hold private information (types are unknown to the seller).
- Mechanism design makes buyers reveal information:
  - Differentiated products (menu of prices)
  - Quantity discounts
- Propose using incomplete information to identify unobserved consumer types:
  - Consumers have unit demands.
  - Product is homogeneous.
- Well suited for airlines:
  - No arbitrage opportunities.
  - Price dispersion and consumer heterogeneity.
  - Data on a large number of markets.

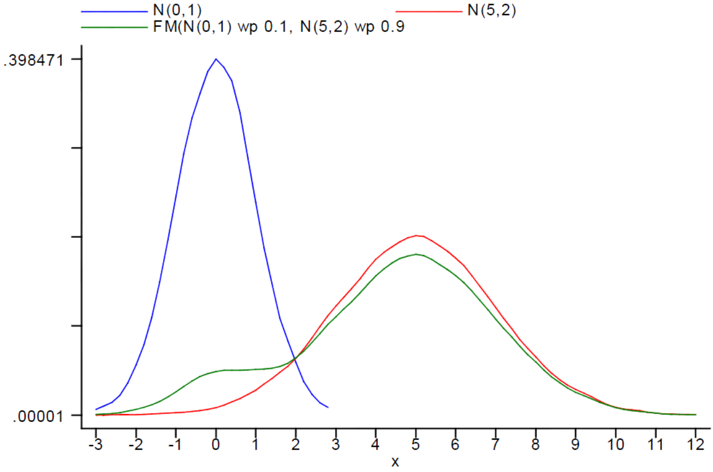
Mixtures: Graphical View



Mixtures: Graphical View



Mixtures: Graphical View



Contribution and Intuition

- Use mixtures to identify consumer types.
- High types (business travelers) have:
  - Less price-sensitive demand.
  - Have higher valuations.
  - Pay higher prices.
- Larger within-type sales dispersion in low types (greater consumer heterogeneity)
- Probability of high-types increases with:
  - Higher capacity utilization.
  - Closer to departure (when fares are low).
  - Income.
  - At hub airports.
  - Market concentration.

Construction of the Data

- Posted prices from *expedia.com*
- Pick a single day: Thursday, June 22, 2006.
  - Controls for systematic peak load pricing.
- One-way, non-stop, economy-class.
  - Connecting passengers / sophisticated itineraries / legs.
  - Uncertainty in the return portion of the ticket.
  - Saturday-night-stayover / min- and max-stay.
  - Fare classes (e.g. coach, first class).
- Panel with 228 cross sectional observations (city pairs).
- Collected every 3 days with 35 observations in time.
- American, Alaska, Continental, Delta, United and US Airways.

Expedia

Summary Statistics

Table: Summary Statistics

VARIABLE	mean	sd	min	max
Monopolies:				
FARE (P)	322.6	171.7	64	914
DAYS	50.8	29.3	1	100
LOAD	0.544	0.245	0.013	1
SALES (Q)	0.017	0.038	-0.392	0.485
$\mathrm{I}_{\mathrm{FARE}>\overline{\mathrm{FARE}}}$	0.349	0.477	0	1
$\mathrm{I}_{\mathrm{LOAD}>\overline{\mathrm{LOAD}}}$	0.427	0.495	0	1
Full sample:				
FARE (P)	292.2	172.3	54	1,224
DAYS	50.8	29.3	1	100
LOAD	0.513	0.250	0.013	1
SALES (Q)	0.017	0.042	-0.408	0.485
INCOME	35,580.0	4619.4	25,198	53,430.0
LEISURE	0.070	0.256	0	1
SLOT	0.298	0.458	0	1
HUB	0.737	0.440	0	1
DISTANCE	1104.4	620.7	91	2,604
HHI	0.679	0.289	0.253	1
$\mathrm{I}_{\mathrm{FARE}>\overline{\mathrm{FARE}}}$	0.340	0.474	0	1
$\mathrm{I}_{\mathrm{LOAD}>\overline{\mathrm{LOAD}}}$	0.416	0.493	0	1

Note: The number of observations is 3,243 for the monopolies and 7,705 for the full sample.

Average and standard deviation of fares

- Prices as the flight date nears

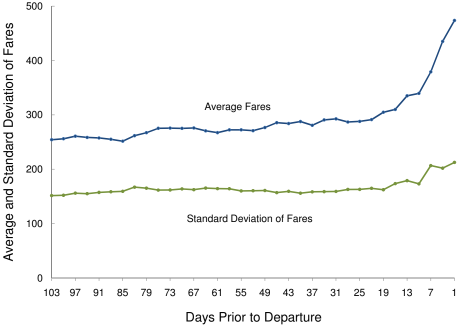


Figure: Average and standard deviation of fares

Demand Equations

N different consumer types:

$$Q_{ijt} = \begin{cases} \alpha_1 + \beta_1 P_{ijt} + X\delta_1 + \kappa_{i,1} + \varepsilon_{ijt,1} & \text{if } \theta = 1, \\ \alpha_2 + \beta_2 P_{ijt} + X\delta_2 + \kappa_{i,2} + \varepsilon_{ijt,2} & \text{if } \theta = 2, \\ \vdots & \vdots \\ \alpha_N + \beta_N P_{ijt} + X\delta_N + \kappa_{i,N} + \varepsilon_{ijt,N} & \text{if } \theta = N, \end{cases}$$

- i: flight; j: route; t: time.
- Unobserved types: $\theta = 1, \ldots, N$
- Q: Sales.
- P: Posted price.
- X: Other factors (days in advance).

Maximum Likelihood

- $\varepsilon_{ijt,\theta} \sim N(0, \sigma^2_{\varepsilon,\theta})$, $\theta = 1, ..., N$, the log-likelihood for the kth flight-time period is:

$$\ln l_k = \ln \left[\sum_{\theta=1}^{N} \frac{r_\theta}{\sigma_{\varepsilon,\theta}\sqrt{2\pi}} \exp\left(\frac{-\varepsilon^2_{k,\theta}}{2\sigma^2_{\varepsilon,\theta}} \right) \right]$$

- where r_θ is the mixing parameter defined as the probability of being in a regime dominated by type θ consumers.
- $\sum_{\theta=1}^{N} r_\theta = 1$

Maximum Likelihood

- Each kth observation can be associated to a particular demand regime θ, $\theta = 1, ..., N$, with probability r_θ.
- We can model the probability of being in a type-θ demand as,

$$r_\theta = \frac{\exp\left(G\delta_\theta\right)}{1 + \sum_{s=1}^{N-1} \exp\left(G\delta_s\right)}$$

- G: Observables that can help us identify the type.

Maximum Likelihood Estimates: Price Discrimination

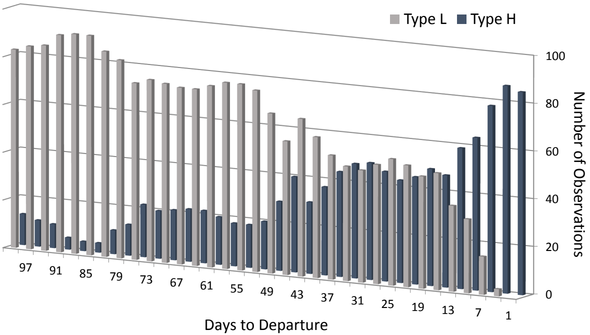
Table: Maximum Likelihood Estimates: Price Discrimination

Model:	(1)	(2)	
Type θ:	Pooled	H	L
Demand Equations:			
CONSTANT	1.6840*	0.0737	3.7413*
	(0.1496)	(0.0955)	(0.3788)
LNFARE	-2.3664*	-1.4578*	-2.6381*
	(0.3409)	(0.1581)	(0.9031)
DAYS	-0.0332*	-0.0175*	-0.0491*
	(0.0027)	(0.0014)	(0.0065)
σ_ε	3.7172*	1.1275*	5.5912*
	(0.0485)	(0.0380)	(0.1361)
Probability of Type H, $r_H = \text{Prob}(\theta = H)$:			
$\mathrm{I}_{\text{FARE} > \overline{\text{FARE}}}$		0.7376*	
		(0.1138)	
Average Fare	322.6	381.6	290.9
Observations	3,243	3,243	
Log likelihood	6,075.1	7,106.9	
SBIC[a]	-3.737	-4.360	

Note: The dependent variable is SALES $\times$ 100. Standard errors in parentheses. All regressions control for flight fixed effects. ‡ significant at 10%; † significant at 5%; * significant at 1%. [a] Schwarz Bayesian Information criterion.

Probability of type-H demand

Figure: Number of observations by type and days in advance



Determining the Number of Types N and Recovering Valuations

Determining the Number of Types N

Table: Determining the Number of Types N

Number of types N	SBIC[a]	Log likelihood	LR test[b]
1	-3.737	6075.057	
2	-4.360	7106.864	0.000
3	-4.351	7111.356	0.110
4	-4.340	7114.844	0.222
5	-4.331	7119.636	0.088

Note: [a] Schwarz Bayesian Information criterion. [b] p-value of likelihood ratio (LR) test reported.

Recovering Valuations

- Reservation values are uniformly distributed $[0, \bar{v}_\theta]$.
- Demand is: $Q = N_\theta - N_\theta / \bar{v}_\theta P$.
- The number of consumers of each type is $N_\theta = \alpha_\theta + X\delta_\theta$.

$$\bar{v}_\theta = -\frac{\alpha_\theta + X\delta_\theta}{\beta_\theta}.$$

Maximum Likelihood Estimates: Reservation Values

Table: Maximum Likelihood Estimates: Reservation Values

Model:	(1)	(2)	
Type θ:	Pooled	*H*	*L*
Demand Equations:			
CONSTANT	1.6529*	0.0787	3.6683*
	(0.1425)	(0.0917)	(0.3607)
FARE	-0.0074*	-0.0046*	-0.0076*
	(0.0010)	(0.0005)	(0.0025)
DAYS	-0.0326*	-0.0174*	-0.0475*
	(0.0025)	(0.0014)	(0.0063)
σ_ε	3.7190*	1.1356*	5.6126*
	(0.0475)	(0.0365)	(0.1326)
Probability of Type H, $r_H = \mathrm{Prob}(\theta = H)$:			
$\mathrm{I}_{\text{FARE} > \overline{\text{FARE}}}$		0.7602*	
		(0.1096)	
Reservation Values:	554.3	692.8	546.4
Average Fare	322.6	381.6	290.9
Observations	3,243	3,243	
Log likelihood	6,073.5	7,106.3	
SBIC[a]	-3.736	-4.360	

Note: The dependent variable is SALES $\times$ 100. Standard errors in parentheses. All regressions control for flight fixed effects. ‡ significant at 10%; † significant at 5%; * significant at 1%. [a] Schwarz Bayesian Information criterion.

Maximum Likehood Estimates: Role of Capacity

Table: Maximum Likelihood Estimates: Role of Capacity

Model:	(1)		(2)	
Type θ:	H	L	H	L
Demand Equations:				
CONSTANT	0.0838	3.4119*	0.1491	3.5532*
	(0.1080)	(0.3692)	(0.1003)	(0.4205)
LNFARE	-1.4496*	-3.4422*	-1.4359*	-2.8008*
	(0.1972)	(0.9093)	(0.1878)	(1.0884)
DAYS	-0.0170*	-0.0431*	-0.0172*	-0.0436*
	(0.0016)	(0.0072)	(0.0015)	(0.0082)
σ_ε	1.1453*	5.7486*	1.2375*	6.0606*
	(0.0523)	(0.1687)	(0.0457)	(0.1901)
Probability of Type H, $r_H = \mathrm{Prob}(\theta = H)$:				
$\mathrm{I}_{\text{FARE} > \overline{\text{FARE}}}$			1.1533*	
			(0.1450)	
$\mathrm{I}_{\text{LOAD} > \overline{\text{LOAD}}}$	0.9974*		0.6630*	
	(0.1930)		(0.1687)	
$\text{DAYS} - \overline{\text{DAYS}}$	0.0261*		0.0303*	
	(0.0031)		(0.0032)	
Observations	3,243		3,243	
Log likelihood	7,137.0		7,180.3	
SBIC[a]	-4.377		-4.401	

Note: The dependent variable is SALES $\times$ 100. Standard errors in parentheses. All regressions control for flight fixed effects. ‡ significant at 10%; † significant at 5%; * significant at 1%. [a] Schwarz Bayesian Information criterion.

Probability of type-H demand

Figure: Probability of type-H demand

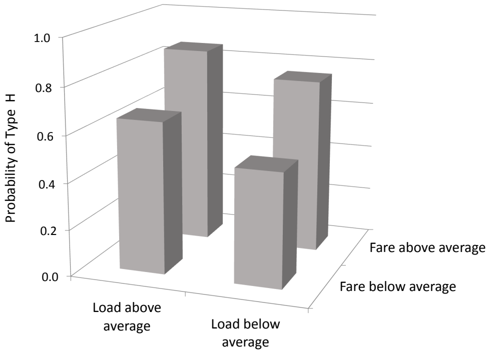


Table: Maximum Likelihood Estimates: Role of Competition

Model:	(1)	(2)		(3)	
Type θ:	Pooled	*H*	*L*	*H*	*L*
Demand Equations:					
CONSTANT	1.8369*	0.0322	3.8670*	0.0632	3.5123*
	(0.1071)	(0.0664)	(0.2842)	(0.0733)	(0.2773)
LNFARE	-1.7219*	-1.0358*	-2.0037*	-0.9848*	-2.0272*
	(0.2048)	(0.1055)	(0.6350)	(0.1136)	(0.6096)
DAYS	-0.0362*	-0.0177*	-0.0522*	-0.0170*	-0.0443*
	(0.0018)	(0.0010)	(0.0050)	(0.0010)	(0.0057)
σ_ε	4.0316*	1.1038*	6.0516*	1.1661*	6.4194*
	(0.0343)	(0.0267)	(0.1003)	(0.0308)	(0.1381)
Probability of Type *H*, $r_H = \text{Prob}(\theta = H)$:					
$\mathrm{I}_{\text{FARE}>\overline{\text{FARE}}}$		0.5266*		0.9872*	
		(0.0750)		(0.0836)	
$\mathrm{I}_{\text{LOAD}>\overline{\text{LOAD}}}$				0.5496*	
				(0.1112)	
$\text{DAYS} - \overline{\text{DAYS}}$				0.0327*	
				(0.0020)	
Observations	7,705	7,705		7,705	
Log likelihood	13,807.7	16,471.5		16,713.5	
SBIC[a]	-3.579	-4.265		-4.326	

Note: The dependent variable is SALES $\times$ 100. Standard errors in parentheses. All regressions control for flight fixed effects. ‡ significant at 10%; † significant at 5%; * significant at 1%. [a] Schwarz Bayesian Information criterion.

Role of Route Characteristics

Table: Maximum Likelihood Estimates: Role of Route Characteristics

Model:	(1)		(2)		(3)	
Type θ:	H	L	H	L	H	L
Demand Equations:						
CONSTANT	0.7170*	5.9771*	0.7208*	6.0161*	0.7209*	6.0107*
	(0.0670)	(0.5449)	(0.0712)	(0.6588)	(0.0680)	(0.6936)
LNFARE	-1.3195*	-2.8756*	-1.3209*	-2.8989*	-1.3235*	-2.8985†
	(0.1133)	(1.0855)	(0.1132)	(1.0175)	(0.1139)	(1.1793)
DAYS	-0.0239*	-0.0749*	-0.0239*	-0.0754*	-0.0239*	-0.0754*
	(0.0011)	(0.0103)	(0.0012)	(0.0109)	(0.0011)	(0.0124)
σ_ε	1.6183*	8.6465*	1.6228*	8.6719*	1.6220*	8.6680*
	(0.0343)	(0.2396)	(0.0325)	(0.2531)	(0.0319)	(0.2706)
Probability of Type H, $r_H = \mathrm{Prob}(\theta = H)$:						
LNINCOME	0.1521*		0.1354*		0.1253†	
	(0.0062)		(0.0096)		(0.0589)	
LEISURE	-0.0695		-0.0004		-0.0855	
	(0.1742)		(0.1649)		(0.2126)	
SLOT			-0.0447		0.0569	
			(0.0928)		(0.1301)	
HUB			0.2679*		0.2663†	
			(0.0963)		(0.1095)	
LNDISTANCE					-0.0292	
					(0.0839)	
HHI					0.4188†	
					(0.1717)	
Observations	7,705		7,705		7,705	
Log likelihood	16,875.4		16,880.2		16,883.8	
SBIC[a]	-4.369		-4.368		-4.366	

Note: The dependent variable is SALES $\times$ 100. Standard errors in parentheses. All regressions control for flight fixed effects. ‡ significant at 10%; † significant at 5%; * significant at 1%. [a] Schwarz Bayesian Information criterion.

Potential Endogeneity of Fares

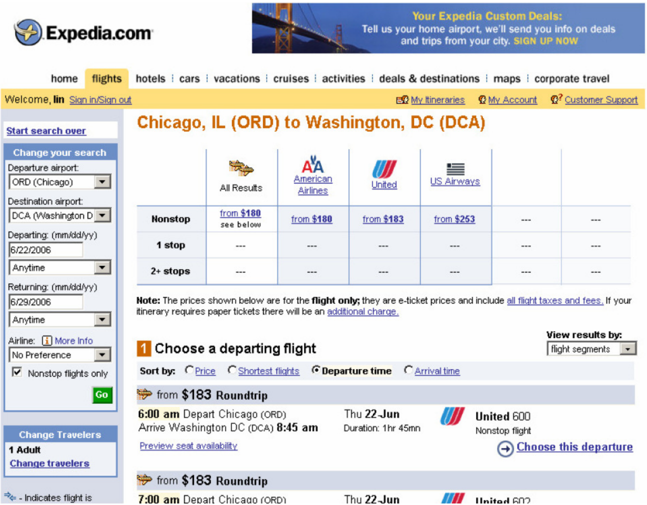
Table: Hausman Test for Potential Endogeneity of Fares

Dependent variable:	LnFare
First Stage Regressions:	
Lag LnFare	-0.0329*
	(0.0044)
Days	-0.0008*
	(0.0001)
Constant	0.2413*
	(0.0279)
Observations	3,145
Underidentification test:	
Kleibergen-Paap rk LM statistic	53.189
$\chi^2(1)$ P-val	0.000
Weak identification test:	
Kleibergen-Paap rk Wald F statistic	55.282
Hausman test. H_0: Fare is exogenous	
F(1,3141)	0.349
Prob $>$ F(1,3141)	0.559

Note: Standard errors in parentheses. All regressions control for flight fixed effects. ‡ significant at 10%; † significant at 5%; * significant at 1%.

Conclusion

- Consumers hold information that is unknown to the seller.
- Present mixtures to separate consumer types.
- Does not rely on particular product attributes as a screening device
- Use partial information: capacity utilization and days to departure.
- Evidence of two types of consumers: Low types more closely resemble “tourists” and high types are business travelers.
- We find that high types are less price sensitive, have higher valuations and pay higher prices.
- The proportion of high types increases as the departure date nears.
- High types are more likely to make a purchase when most travelers already booked.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American Airlines
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Nonstop
from $180 see below
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1 stop
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Note: The prices shown below are for the flight only; they are e-ticket prices and include all flight taxes and fees. If your itinerary requires paper tickets there will be an additional charge.
1 Choose a departing flight
View results by:
flight segments
Sort by: Price Shortest flights Departure time Arrival time
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Arrive Washington DC (DCA) 8:45 am
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Nonstop flight
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from $183 Roundtrip
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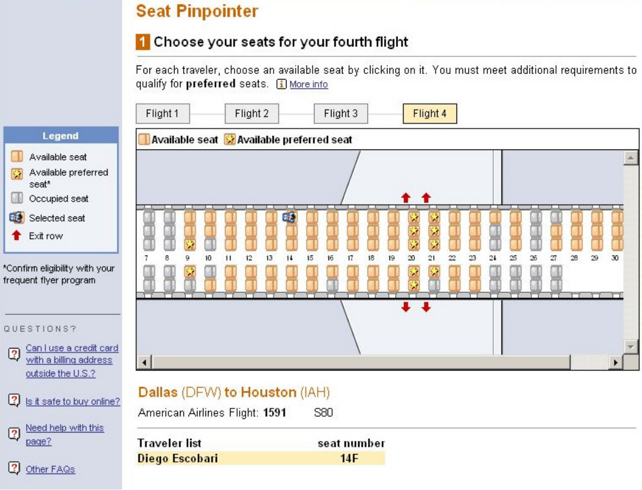
Thu 22-Jun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Dallas (DFW) to Houston (IAH)
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Traveler list
seat number
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14F

Data

Table: Hausman Test to Evaluate the Model Identification

Excluded variables from type equation	H_0: Difference in coefficients of demand equation between benchmark model and alternative models not systematic
$\mathrm{I}_{\textsc{Fare}>\overline{\textsc{Fare}}}$	11.5929 (0.1148)
$\mathrm{I}_{\textsc{Load}>\overline{\textsc{Load}}}$ & $\textsc{Days}-\overline{\textsc{Days}}$	9.4537 (0.2217)

Note: Benchmark model includes $\mathrm{I}_{\textsc{Fare}>\overline{\textsc{Fare}}}$, $\mathrm{I}_{\textsc{Load}>\overline{\textsc{Load}}}$ and $\textsc{Days}-\overline{\textsc{Days}}$ in the type equation. Hausman Chi-squared statistic reported and *p*-value in parentheses.