Organizational Structure and Pricing: Evidence from a Large U.S. Airline

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March 2022

Acknowledgements: Ali and Kevin thank the University of Chicago, Becker Institute, Yale University, the Tobin Center, the OIGI at the F.R.B of Minneapolis, and the NET Institute for supporting this project.

Disclosures: We thank the anonymous airline for giving us access to the data used in this study. Under the agreement with the authors, the airline had “the right to delete any trade secret, proprietary, or Confidential Information” supplied by the airline. We agreed to take comments in good faith regarding statements that would lead a reader to identify the airline and damage the airline’s reputation. All authors have no material financial relationships with entities related to this research.
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- This is true for pricing—often involves complex optimization systems designed around the organizational structure of the firm.
- We investigate team input decisions of an early pioneer in this area.
Airlines face a difficult allocation problem: fixed capacity, uncertain demand, consumers with different WTP.

In the static setting, this allocation problem and its welfare consequences are well understood.

However, dynamic markets are considerably more complex.

Airlines were early adopters of algorithms and designed their organizational structures around them.

There is still active debate regarding the welfare consequences of these systems.
What do we do in this project?

- Pricing is both sophisticated and fragmented
  - Thinks carefully about the opportunity cost of a seat
  - Different organizations having authority/responsibility over different inputs
  - e.g., the team that decides prices does not forecast demand and does not set capacity
  - This isn’t unique to our airline; job listings show all airlines are organized this way (and now hotel and cruise rooms, stadium seats, retailing, etc.)

- Pricing is subject to miscoordination and multiple biases
  - e.g., does not account for cross-price elasticities, uses persistently biased forecasts

- Estimate a model of demand and contrast our predictions with the firm’s forecasts

- We then ask: What would outcomes be without pricing biases?
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Our central findings

- Correcting biases of teams individually does **not** greatly affect CS and revenues.

- Biases are not reinforcing, but they are also not offsetting → not close to second-best optimal (a team best responds to a bias of another team).

- Correcting biases across teams (1st best) leads to very different outcomes: lower prices early on, higher prices close to departure, increased deadweight loss.

- Possible mechanisms: performance metrics, limited transfer of information across teams, limited experimentation.
Connections to the literature

• Organizational Economics:
  − Highlight the problem of “implementation,” problem identified, solution known, managers do not implement

• Behavioral IO:
  − Directly observe pricing frictions

• Market Segmentation, Dynamic Pricing, Airlines:

• Operations:
  − Estimate the effectiveness of these algorithms using airline data
How inputs come together to determine prices: Network Plan., Pricing, RM

1. **Network Planning**
   - Routes Served
   - Frequencies
   - Capacities

2. **Pricing Dept.**
   - Fares
   - Fare Restrictions

3. **RM Dept.**
   - Forecast
   - Pricing Algorithm
   - Historical Shares

4. **Consumers**
   - Observe fares
   - Purchase

**Variables**:
- $C$ is a vector of network parameters
- $p_1, \ldots, p_k$ are the prices
- $IC_1, \ldots, IC_k$ are the historical shares, viewed as $p$
“Pricing” in this context involves both prices and quantities

The heuristic allocates inventory to fares; we select EMSR-b

Central idea: Today, how much capacity do I need for tomorrow assuming all future demand arrives tomorrow?

Optimization idea: MR = MC in this simplified model

All airlines have adopted this organizational structure, but many industries are similar
• Discrete fares $\rightarrow$ 1.5% of fares change; actual “menu cost” for changing

• We do not model the capacity decision
We use novel data from a large international air carrier

Combine five main data tables in order to see all algorithm inputs:

1) Ticketing data—$Q$
   - Sales for all flights for 400+ markets covering 2018-2019
     (similar route selection criteria as in Williams, 2022: many single carrier, mostly nonstop traffic)
   - Details for millions of transactions
   - We focus on nonstop economy class bookings

2) Inventory allocation decisions—$P$
   - How many seats the airline is willing to sell for given prices over time
   - We observe the code; output includes the opportunity cost of a seat
We also observe $E[Q]$, search, fare choices

3) Forecasting data—$E[Q]$
   - Not a complete panel, but 100ks observations per route
   - At the pax. type, departure date, forecasting period, day before departure, price level

4) Clickstream search data—$A$
   - All interactions on the carrier’s website and mobile website (hashed)
   - For this project, we measure arrivals

5) Filed Fares—$F$
   - Daily extracts of all fares filed by the pricing department
   - What fares are possible
Pricing biases and miscoordination

1) (within) Using Persistently Biased Forecasts
   ▶ Forecasts are biased upward in 2 years of data

2) (within) Not Accounting for Cross-Price Elasticities
   ▶ Opportunity cost changes of substitutes has no impact on other product prices

3) (across) Pricing Frictions
   ▶ The use of fare buckets leads to cost changes that do not trigger price adjustments

4) (miscoordination) Allocating Seats to Fares that do not Exist
   ▶ Arises because the pricing department has not told the RM department to remove these fares

5) (miscoordination) Pricing on the Inelastic Side of the Demand Curve
   ▶ According to the demand estimates from the RM department
1) Persistently biased forecasts

- Median forecast 10% higher than actual future demand (predict extra 2.5 seats sold)
- Manual adjustments do not help much
- Low-fare transactions underforecasted by 20%, high-fare transactions overforecasted by 10%.
2) Prices do not respond to the demand of substitutes

- Consider AM and PM flights. The AM flight sells a ticket. What happens to PM flight? Answer: Nothing, because flights are priced independently

(a) No effect of bookings on substitute MC

(b) No effect of bookings on substitute prices

- Understates potential market power
3) Changes in marginal costs do not trigger price adjustments

- (left) Changes in marginal costs occur $3 \times$ as frequently as price adjustments. Spikes: reforecasting periods. Friction: Coarse prices due to the industry use of “fare buckets”

- (right) Probability of a fare change given the change in marginal cost
4) Allocating inventory to fares that do not exist

- Instances in which the pricing team has not informed the RM department to remove fares from the system

- Affects 11.6% of allocations

- In 71% of such instances, the algorithm believes a lower fare is possible

- Persistently affects 32% of routes, typically smaller routes from hubs to spokes
How miscoordination can affect pricing

- Consider two sequential markets s.t. demand equals $Q_1(p_1) = 10 - 10p_1$ and $Q_2(p_2) = 10 - 1p_2$. Initial capacity is 15.

- Optimal prices are $(p_1, p_2) = (0.5, 5)$, and the capacity constraint does not bind.

- Can be obtained using the decentralized system just described: Input correct “forecast” and assign fares to be $\{0.5, 5\}$ and $\{5\}$.

- Crucially, EMSR-b decides the number of seats that can be sold at each input price to ensure that future demand can be satisfied.

- If early period fares are $\{0.2, 0.5, 5\}$, future demand will be satisfied but EMSR-b will choose $p = 0.2$ even though 0.5 is in choice set.
5) Chosen prices are often on the inelastic side of the demand curve

- The RM’s forecasts provide $EQ$, at the flight $(j)$, departure date $(d)$, day before departure $(t)$, price $(p)$ level

- Because we observe the $EQ$ at multiple prices, we simply compute the elasticity and arc elasticity for each observation

- We compare the elasticity at the observed flight prices

- 30%-50% of observations are priced at elasticity levels greater than -1 using the firm’s beliefs about demand

- This is known to RM, but the pricing department does not remove these fares $\rightarrow$ problem of implementation

- Even the best teams are associated with setting “inelastic prices” 30% of the time
Facts that guide modeling decisions

1) Granular market definition
   ▶ 60% of price changes occur before advance purchase fares expire
   ▶ Flights are reoptimized daily

2) Sparsity of sales
   ▶ Over 86% of all sales observations are zero (for any itinerary)
   ▶ The 99th percentile of daily search volume is 14

3) Change in overall demand elasticity
   ▶ The probability you are assigned as “business” increases by $3 \times$ over time

4) Single fare instead of menu
   ▶ Over 90% of consumers purchase the lowest fare

5) Consumers make a static decision
Search patterns

Consumers make a static decision

- 90% of customers search on one day only (non referrals)
- Some repeat shoppers over dif. departure dates, but far apart → different trips
- Expedia, etc. bookings similar to direct channel

**((c)) CDF of Same Itin. Searches**

**((d)) CDF of Similar Itin. Searches**

**((e)) Channel Booking Distributions**
We wish to quantify the welfare impacts of alternative pricing inputs, therefore, we need to estimate demand.

1. **Consumers Arrive at** \( t \) (Poisson arrivals in discrete time)
2. **Consumers decide purchases** (discrete choice)
3. **Demand is realized** (random rationing)
4. **Firm chooses** \( p_{t+1} \) (e.g., solves DP, EMSR-b)

\( t+1 \)
We follow Hortaçsu, Natan, Parsley, Schwieg, and Williams (2022), (builds on Williams, 2022)

Market: origin-destination, departure date, days before departure; \((r, d, t)\)

Individual: \(i\); Consumer type: \(\ell \in \{B, L\}\).

\(Pr_t(\text{business traveler}) = \gamma_t.\)

Utility specification:

\[
\begin{align*}
    u_{i,j,t,d} = \begin{cases} 
    X_{j,t,d} \beta - p_{j,t,d} \alpha \ell(i) + \xi_{j,t,d} + \varepsilon_{i,j,t,d}, & j \in J(t, d) \\
    \varepsilon_{i,0,t,d}, & j = 0
    \end{cases}
\end{align*}
\]

Consumer \(i\) chooses flight \(j\) if, and only if,

\[
u_{i,j,t,d} \geq u_{i,j',t,d}, \quad \forall j' \in J \cup \{0\}.
\]
Model of consumer arrivals

- Arrivals are given by
  \[ A_{t,d} \sim \text{Poisson}\left( \frac{\lambda_{t,d}}{\zeta} \right) \]

- \( \zeta \) scales for unobservable searches \((more \ complicated, \ next \ slide)\)

- Poisson arrivals \( \Rightarrow \) Poisson demand:
  \[ \tilde{q}_{j,t,d} \sim \text{Poisson}\left( \lambda_{t,d} \cdot s_{j,t,d}(p) \right) \]

- Consumers do not know remaining capacity; random rationing

- Demand may be censored, i.e., \( q_{j,t,d} = \min \left\{ \tilde{q}_{j,t,d}, C_{j,t,d} \right\} \)
• In the simplest case, if we observe searches for 50% of bookings, scale arrivals by $2 \times$

• The distribution of bookings on the direct channel changes over time (agency bookings shifted toward departure)

• To account for this, we use the distribution of bookings across channels and an algorithm that classifies all searches/bookings by passenger types

• This defines a scaling factor $\zeta_{t,\ell}$

• We conduct robustness to this specification: does not greatly impact the results, but does decrease the change in arriving consumers over time
Empirical Specification and Estimation

- Cannot estimate arrival rates with $n = 1$; therefore,

$$\lambda_{t,d} = \lambda_t \lambda_d$$

- $X$: DoW effects, week effects, ToD preferences

- $Z$: Ortho. poly. of shadow value of remaining capacity; sum of onward bookings at the D (or O) airport; advance purchase indicators

- Draw from posterior distribution of model parameters with Hybrid Gibbs Sampler
  (adapting Jiang, Manchanda, and Rossi (2009) to discrete random coefficients, Poisson demand, and censored demand)
Structure of Price Endogeneity

• We allow for price-setting that incorporates the demand shock, $\xi$

• Using a set of instruments $Z_{j,t}$, we specify a linear pricing equation

$$p_{j,t} = Z'_{j,t} \eta + \nu_{j,t}.$$ 

• Semi-parametrically control for price endogeneity using a finite normal mixture model with classifier fixed by booking horizon

• Extension available for estimation of joint distribution using Dirichlet Process prior

• Approach can be robust to multiple equilibria via extension to allow $\eta$ to come from a finite mixture
Algorithm 1 Hybrid Gibbs Sampler

1: for \( c = 1 \) to \( C \) do
2:   Update arrivals \( \lambda \) (Gibbs)
3:   Update shares \( s(\cdot) \) (Metropolis-Hastings)
4:   Update price sensitivity parameters \( \alpha \) (Metropolis-Hastings)
5:   Update consumer mix \( \gamma \) (Metropolis-Hastings)
6:   Update linear parameters \( \beta \) (Gibbs)
7:   Update pricing equation \( \eta \) (Gibbs)
8:   Update mixture component parameters \( \Sigma_k, \mu_k \) (Gibbs)
9: end for
Recovering demand the firm believes it faces—Model B (“Beliefs”)

- What preference parameters are consistent with the RM dept.’s forecast?

- Using the passenger assignment algorithm on searches, we estimate

\[ \text{Pr}_t(\text{business}) := \gamma^\text{beliefs}_t = \frac{\text{Arrivals}^B_t}{\text{Arrivals}^B_t + \text{Arrivals}^L_t}, \]

- We can then recover arrival rates \(= \tilde{\lambda}^\ell_{t,d} \)

- Therefore, we use the forecasting data to recover \(\tilde{\delta}_j\):

\[ E[Q^\ell_{j,t,d,p}] = \tilde{\lambda}^\ell_{t,d} \cdot s^\ell_{j,t,d,p} \]

Arrival Rate · Purchase Probability

- We invert (Berry 94, BLP 95) to recover \(\tilde{\delta}_j\)
• Model E identifies consumer types as being more similar
• Model B suggests a more significant shift in arriving customers over time
• Substantial differences in the predicted # of late-arriving business customers
Comparing our demand estimates to firm beliefs, Model E vs Model B

((g)) Demand 60 Days Out

((h)) Demand 7 Days Out

- (h): Model B produces higher leisure demand and lower business demand
- (i): Model E produces higher demand for very high prices due to business customers
Returning to miscoordination: Are prices sometimes too low?

- We analyze how compatible fares are with Model B demand.

- Consider the extreme case: capacity costs are zero.

- Then, the optimal price solves $MR(p) = 0$ of the static problem.

- Are prices above or below these values?

- Findings:
  1) 50% of filed fare menus contain fares below the threshold.
  2) 85% of menu fares are above the threshold.
  3) 30% of observed fares are below the threshold.
Counterfactual setup for welfare analysis

<table>
<thead>
<tr>
<th>(1) Model B, Observed Fares</th>
<th>(3) Model E, Observed Fares</th>
</tr>
</thead>
<tbody>
<tr>
<td>(2) Model B w/ Fares coord. to Model B</td>
<td>(4) Model E w/ Fares coord. to Model E</td>
</tr>
</tbody>
</table>

- (2) and (3): Address a single bias, leave others unchanged
- (4) Correct and coordinate inputs
- Coordinated fares: Lowest price solves $MR(p) = 0$, then increase by a factor
Welfare estimates under alternative pricing systems

<table>
<thead>
<tr>
<th>Counterfactual</th>
<th>CSL</th>
<th>CSB</th>
<th>Q</th>
<th>Rev</th>
<th>W</th>
</tr>
</thead>
<tbody>
<tr>
<td>1) Observed Fares, Model B Forecast</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
<td>100.0</td>
</tr>
<tr>
<td>2) Observed Fares, Model E Forecast</td>
<td>99.9</td>
<td>99.8</td>
<td>99.7</td>
<td>101.9</td>
<td>100.6</td>
</tr>
<tr>
<td>3) Altered Fares to Model B Forecast</td>
<td>69.4</td>
<td>102.7</td>
<td>85.4</td>
<td>93.0</td>
<td>97.3</td>
</tr>
<tr>
<td>4) Altered Fares to Model E Forecasts</td>
<td>121.0</td>
<td>64.1</td>
<td>92.3</td>
<td>118.6</td>
<td>86.6</td>
</tr>
</tbody>
</table>

- (1) and (2) similar because EMSR-b understates opportunity costs s.t. min filed fare open
- (3) actually worse because composition of demand is off
- (4) different because min filed fare adjusts to correct WTP; early prices too high and late prices too low
- Central finding: Outcomes change only if all inputs are adjusted
Quantifying second-best outcomes

- Where are 2nd-best outcomes relative to observed and 1st best?

- We perform two exercises:
  1) What if the pricing department knew Model E → adjusts menu; RM dept. does not alter input
  2) What if the revenue management department scales up/down forecast (within Model B); pricing dept. does not alter input

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<th>$CS_B$</th>
<th>$Q$</th>
<th>$Rev$</th>
<th>$W$</th>
</tr>
</thead>
<tbody>
<tr>
<td>5) Pricing Department uses Model E forecast</td>
<td>122.5</td>
<td>64.0</td>
<td>92.7</td>
<td>117.6</td>
<td>86.4</td>
</tr>
<tr>
<td>6) RM Department manipulates Model B forecast</td>
<td>77.7</td>
<td>94.0</td>
<td>89.7</td>
<td>106.2</td>
<td>97.2</td>
</tr>
</tbody>
</table>

- Using upstream decision to “correct” downstream decision nears 1st best; accounting for changes in WTP is very important

- Using downstream decision to “correct” upstream decision more difficult
Mechanisms

- Performance metrics: In over half the calls, all major airlines emphasize load factor → opposite direction of CF results

- Forecast bias: Forecast should be *more* biased in 2nd best CF → improbable that bias of 700% is accepted

- Limited information transmission: Substantial costs to adjust organizational structure?

- Long-run demand: Pricing algorithm, forecasts, and forecasting technology all think about the short run

- Limit pricing: Biases are even more pronounced in competitive markets
Concluding thoughts

- We document biases within and across teams in pricing at a large U.S. firm

- Example of the problem of “implementation” in organizational economics

- Causes? Reporting statistics, under-experimentation, lack of information transfer?

- Miscoordination in pricing inputs has significant consequences on the allocation of capacity

- Leisure travelers benefit; business customers are harmed under 1st best; quantity declines and dead-weight loss increases
Thank you!
How to simplify the airline pricing problem? Remove the dynamics

- EMSR-b belongs to a class of static solution heuristics

- Central idea: Today, how much capacity do I need for tomorrow assuming all future demand arrives tomorrow?

- Optimization idea: Equate marginal revenue to the opportunity cost of a seat

- Lowest prices are assumed to sell first (overwhelmingly true in the data)

- EMSR-b creates a composite price $(p_c)$, weighted by forecasts

- Algorithm returns sales limits $b_k$ for every price $k$, by solving

$$1 - F_{Demand}(Capacity - b_k) = \frac{p_k}{p_c}$$
Simulation details:

- 10,000 flights for a draw of preferences ($D$) and remaining capacities ($RC$)
- $\neg j$ prices assumed to be charged at $\min F_t$; recall EMSR-b is for a single product
- Once $J$ prices solved for, demand is simulated according to demand estimates
- We randomly sort arriving customers; presented with min. price avail.
- For the last period, we assume inventory allocation is kept constant; EMSR-b is not defined in the terminal period