

Discriminatory Pricing In The Airline Industry

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March 26, 2025



Introduction

Firms often use discriminatory pricing strategies to increase profits through surplus extraction.

- Technological innovation allows for increasingly sophisticated discriminatory pricing.

The welfare implications of such strategies is often ambiguous [Bergemann et al., 2015] and empirical research is needed to understand impact to profits and consumers.

Using novel data obtained from a partnership with a North American airline, my dissertation seeks to understand discriminatory pricing strategies in the airline industry.

My dissertation consists of two chapters that:

- ① Analyze the role of “upgrades” to airlines and quantifies their effect on profit and welfare.
- ② Examine what search data reveals to airlines and researchers about consumer behavior.

1 Search Data:

- Web traffic data from the airline's website
- All flight searches and purchases from the airline's website, including redirected traffic e.g. Google Flights, Kayak

2 Revenue Management Data:

- Aircraft cabin capacities and flight information
- Daily ticket sales and transaction prices

3 Upgrade Data:

- Bids placed for upgrades, outcomes of bids, and other auction info
- Upgrades purchased at check-in including price

Chapter 2: Should I Stay or Should I Go? An Empirical Analysis of Consumer Behavior Using Airline Web-Traffic Data

“If I go, there will be trouble, and if I stay, it will be double,
So come on and let me know, this indecision's bugging me”

— The Clash

What Can We Learn About Consumers From Searches?

Consumers often search for products online with search engines or on company websites.

- Generates web-traffic data that may reveal information about consumer demand and behavior

Search data can serve a unique role in demand estimation by identifying increasing arrivals separately from more inelastic demand.

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"The key identification challenge of the paper is to separately identify the demand parameters from the arrival process. This challenge was pointed out in Talluri and van Ryzin [2004], for example. The issue arises because without proprietary search data to pin down the arrival process, an increase in arrivals could instead be inferred as inelastic demand."

— Williams [2022]

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Search data can serve a unique role in demand estimation by identifying increasing arrivals separately from more inelastic demand.

This research uses proprietary web-traffic data from a North American airline's website as well as Google Flights to examine what it reveals about consumers.

Contributions:

- ① Shows how revenue-management practices impact consumers
- ② Test assumptions used in empirical models of airlines and consumer search
- ③ Measure the importance of factors influencing consumer choice

Methodological Approach and Notable Findings

To understand how consumer characteristics affect timing, purchase, and pricing, we

- Describe how consumer observables are related to each outcome.
- Regress search timing, purchase decisions, and prices on observables.

Notable findings include:

- ① Searches, bookings, and conversion rates increase approaching departure
 - Explained mostly by consumer observables
- ② Searches for one-way, premium tickets and by solo frequent fliers are closer to departure
 - Purchase at highest rate
- ③ Families and multi-adult parties arrive much earlier to pay lower fares
 - Purchase at lowest rate
- ④ Strong heterogeneity in purchased prices across consumer and market characteristics
 - Markets with more competition see lower conversion rates

Chapter 1: Revenue Management with Reallocation

“On my way home I'll bump this seat right up to first class,
So I can drink that cheap champagne out of a real glass.”

— Dierks Bently, *Drunk On A Plane*

Price Discrimination Using Upgrades

Firms in the travel and leisure industries often allow consumers to “upgrade”

- Swap their initial purchase with a higher quality good
- Mechanisms include loyalty programs, fixed prices, and auctions.

Upgrades present a trade-off to the firm:

- Allows for reallocation of remaining capacities while collecting additional revenue (+)
- Risks drawing consumers away from purchasing higher quality good at full price (-)

This research estimates an equilibrium model of airline and consumer behavior to quantify the impact of upgrades on profits and welfare.

Contributions:

- ① First to analyze upgrade auctions and quantify welfare impacts of upgrades
- ② Developed novel algorithm for solving equilibrium beliefs which can be used in future work

Structural Model Overview

Monopoly airline sells seats in two vertically differentiated cabins to maximize expected profits

- Sets cabin-specific prices and releases seats each period before departure
- Permits bids for upgrades at time of purchase and chooses winning bids at pre-determined time before departure
- Offers remaining premium seats for fixed price at departure

Consumers decide between premium, economy, and no purchase.

- Upgrades create option value for economy purchases
- Consumers are strategic and choice based on beliefs about others' actions and airline's pricing and bid-acceptance policies

Solution to Structural Model

A solution to the model yields two sets of objects:

- 1 Policies, $p_t(\mathbf{k})$ and $\bar{q}_t(\mathbf{k})$, that solve pricing team's dynamic program.
- 2 Beliefs, $\varrho_t(\mathbf{k})$ and $\varphi_t(\mathbf{k})$, that form a PBNE in game between upgrade team and consumers.

Consistent with airline's DGP, first solve for $p_t(\mathbf{k})$ and $\bar{q}_t(\mathbf{k})$, then solve $\varrho_t(\mathbf{k})$ and $\varphi_t(\mathbf{k})$

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- Solving for $p_t(\mathbf{k})$ and $\bar{q}_t(\mathbf{k})$ is the same as in Aryal et al. [2023]
- However, solving for $\varrho_t(\mathbf{k})$ and $\varphi_t(\mathbf{k})$ requires some innovation

Overcoming Challenge of Solving Equilibrium Beliefs

Consumers' beliefs of being upgraded in the future influence *expected utility* of economy

$$\text{Economy Expected Utility} \quad \mathcal{U}_t^e = \underbrace{\nu - p_t^e}_{\text{Certain utility}} + \underbrace{\varrho_t^*(k)(\nu(\xi-1) - b^*)}_{\text{Auction utility}} + \overbrace{\left(1 - \varrho_t^*(k)\right) \varphi_t(k) \max \{0, \nu(\xi-1) - r\}}^{\text{Check-in utility}}$$

Willing to pay check-in

Cabin choice compares \mathcal{U}_t^e with certain utilities $u_t^f \equiv \nu\xi - p_t^f$ and $u_t^o \equiv 0$

- Therefore, upgrade beliefs can alter initial choice of cabin

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Developed an iterative forward-simulation procedure to solve numerically:

- 1 Forward simulate R sequences of decisions given initial beliefs
- 2 Calculate upgrade probabilities given airline's bid-acceptance policy
- 3 Update initial beliefs to equal upgrade probabilities
- 4 Iterate steps 1, 2, and 3 until convergence to a fixed point

Estimation: Overview

Model's data-generating process (DGP) for a flight has two components:

- 1 Market arrival process: $\Lambda_m = \{\lambda_{mt}\}_{t=1}^T$
 - λ_{mt} is period t 's arrival rate for market $m \in \{1, \dots, 27\}$

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- 2 Consumer parameters: $\psi = (\mu_\nu^L, \mu_\xi^L, \mu_\nu^B, \mu_\xi^B, \Delta_\gamma)$
 - For travelers $\omega \in \{L, B\}$, μ_ν^ω is mean WTP for travel, μ_ξ^ω is mean preference for quality
 - Δ_γ is a per-period increase in $\Pr(\omega = B)$ for each traveler.

Estimation: Overview

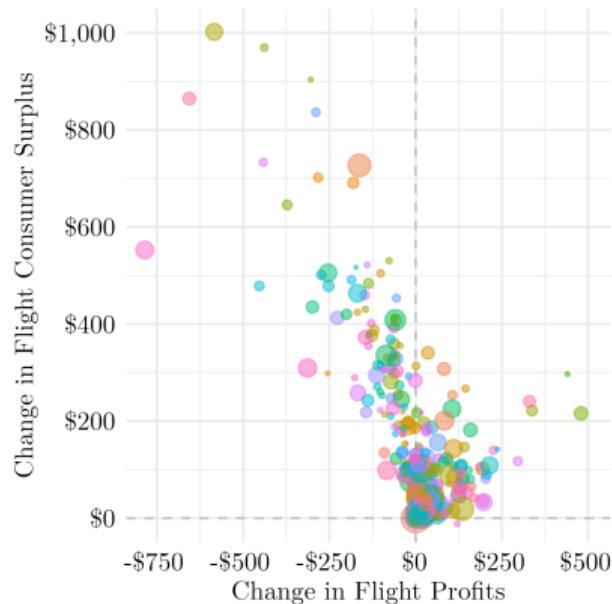
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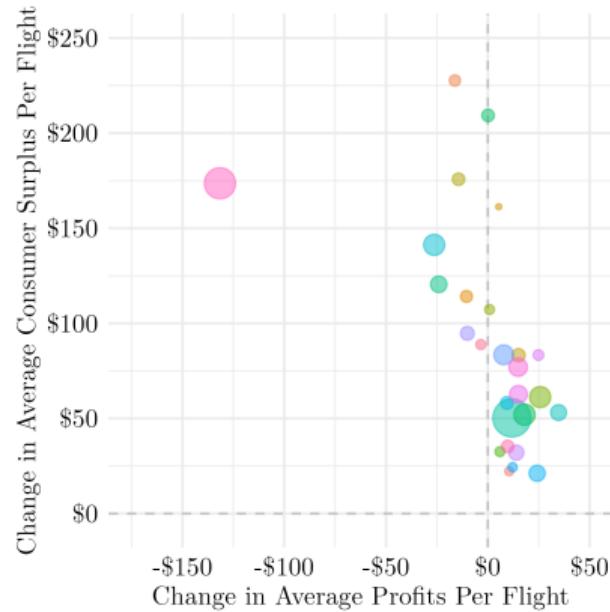
Estimate flexible distribution of demand across flights *within each market* using moment-based approach of Fox et al. [2016], Nevo et al. [2016]

- Separates computation and estimation steps:
 - 1 First solve model for grid of “candidate” DGPs (entirely computation)
 - 2 Estimate weights by averaging across simulated model moments to match data moments
- Results in a discrete distribution of flights that captures heterogeneity in market

Counterfactual: Impact of Upgrades on Profits and Consumer Surplus



a Candidate DGPs



b Market Averages

- Upgrades modestly increase welfare, split between profit and CS depends
- Change to average profits in a market depends but is modest

Conclusion

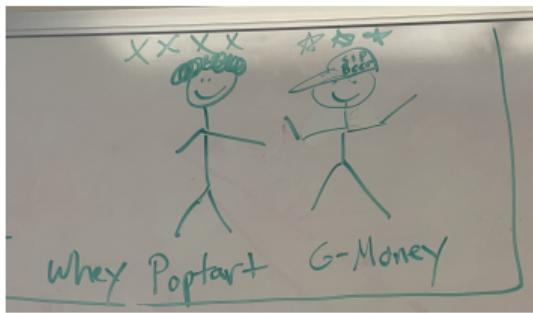
This work makes multiple contributions to our understanding of price discrimination.

- I am particularly proud of the code that solves the equilibrium beliefs.

Future plans for this work:

- Chapter 2 has been accepted at *Economics of Transportation*
- Tweak structural model in Chapter 1 to better fit data and run additional counterfactuals.
 - Plan to submit to top journals.
- Finish companion paper to Chapter 1 that extends model to uninformed consumers.

Thank You!



Appendix

Price Descriptives

Variable	Mean	Transactions			Domestic			
		25 th	50 th	75 th	Mean	25 th	50 th	75 th
Economy:								
Fare (<i>per direction</i>)	212.46	122.44	183.59	269.42	231.88	139.49	205.11	288.32
Observations	732,859				3,870,043			
Premium:								
Fare (<i>per direction</i>)	521.73	377.68	481.38	623.40	617.05	416.42	534.68	760.04
Observations	37,810				139,821			

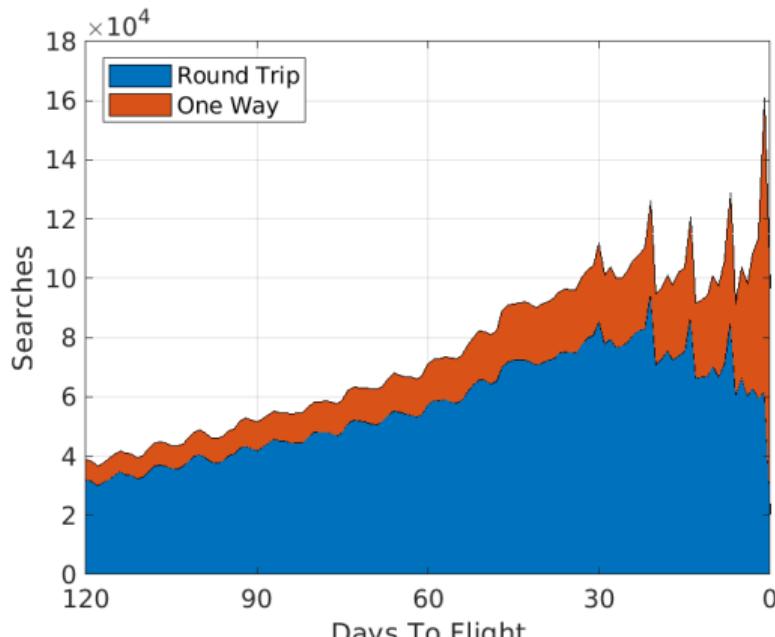
- Economy prices lower than premium prices (same true for international)
- Transaction price lower than quoted prices with larger upper tail

Conversion Rate Descriptives

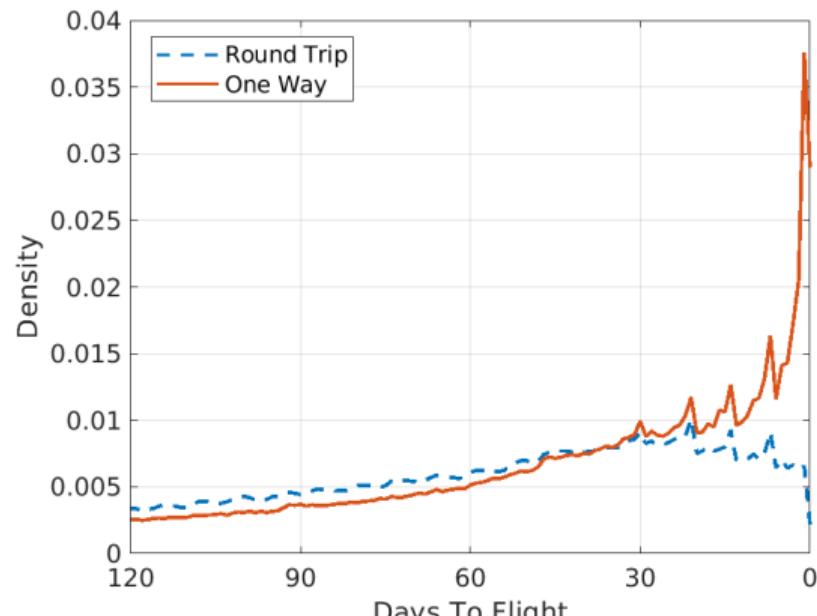
Variable	Share	Conversion Rate	
		I = 1	I = 0
Itinerary:			
Domestic	0.396	0.161	0.072
Economy	0.948	0.106	0.124
Round Trip	0.782	0.082	0.197
Travel Party:			
Single Adult	0.519	0.132	0.081
Family	0.110	0.067	0.112
Loyalty Status:			
Not Logged In	0.599	0.048	0.196
Tier 1	0.336	0.188	0.067
Tier 2	0.027	0.203	0.105
Tier 3+	0.019	0.238	0.105

- Substantial variation in conversion rates by groups.

Increasing Arrival Rates: One way vs Round Trip



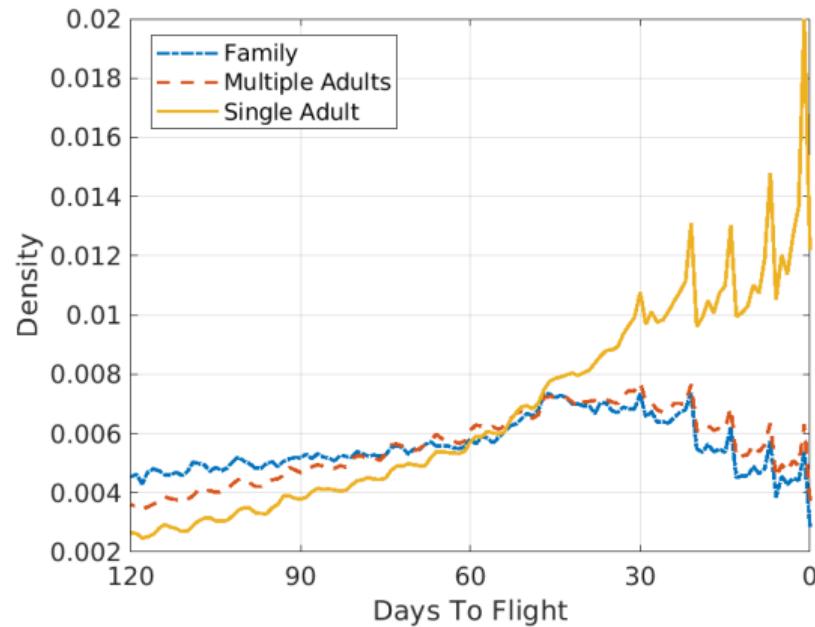
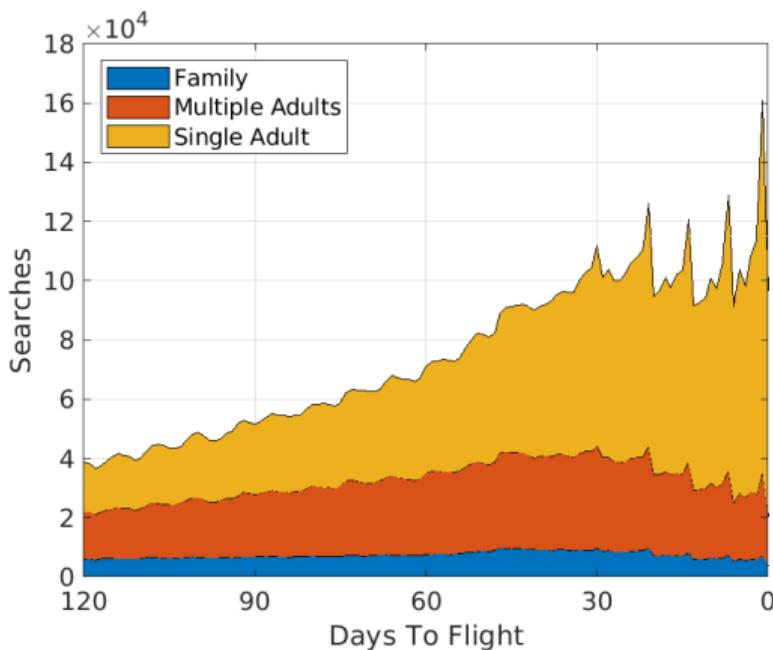
Searches



Density

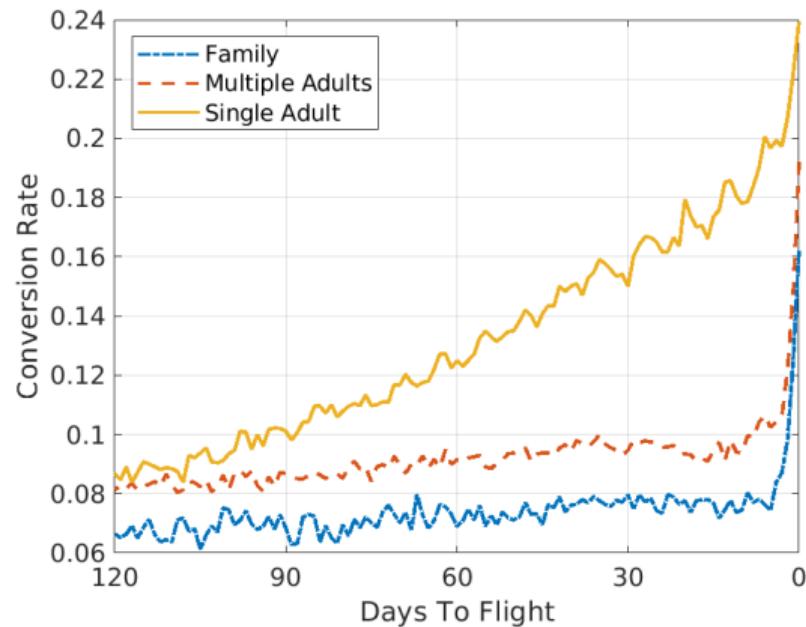
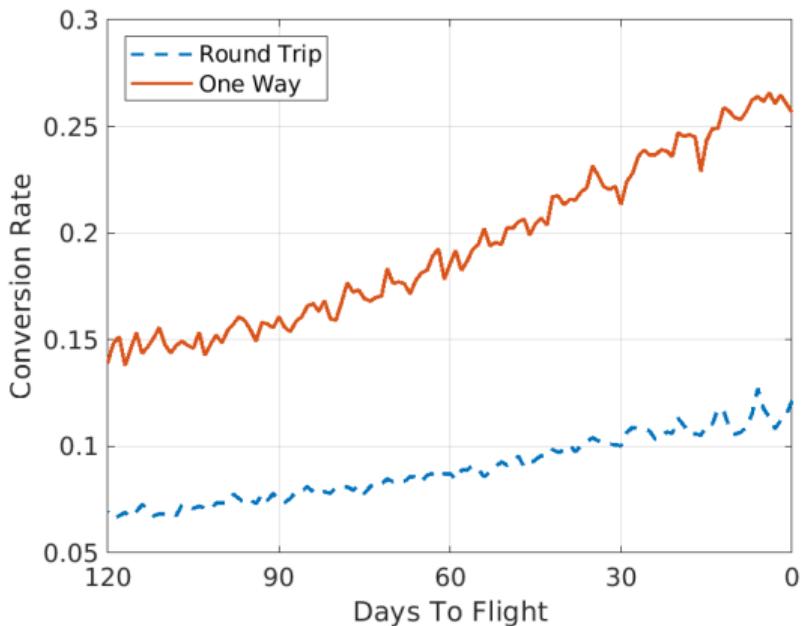
- Total searches peak around 30 days out. One way trips peak at departure.

Increasing Arrival Rates: Party Size



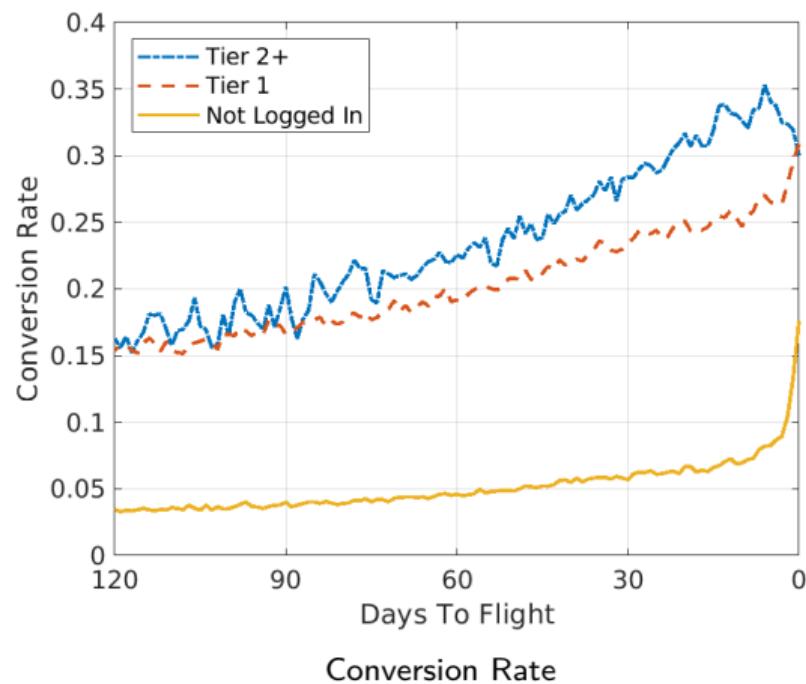
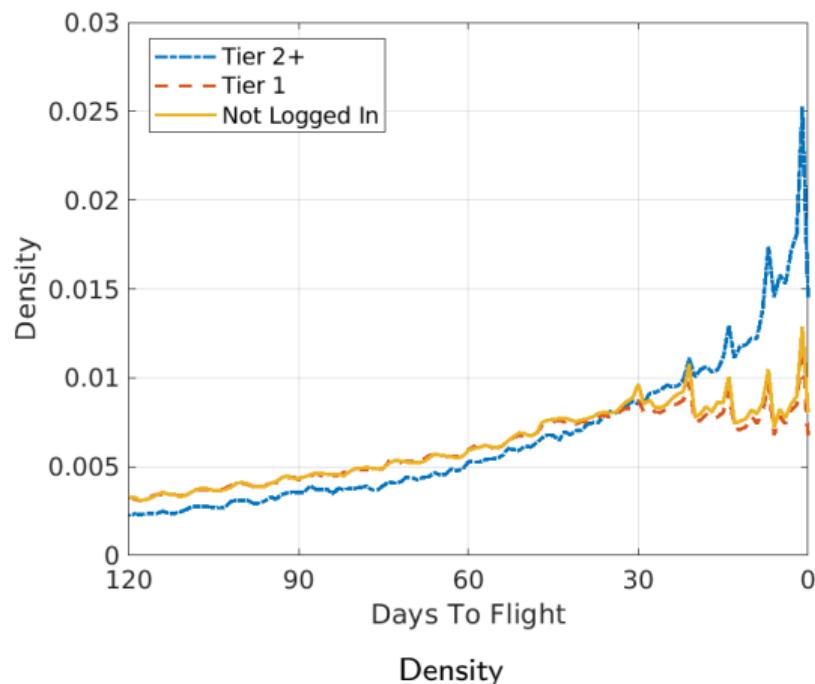
- Total Searches peak around 50 days out. Single adult density increase towards departure.
- Single adults resembles one way travelers (unsurprising)

Evidence of Higher WTPs Near Departure: Conversion Rates



- Trip Type
 - Conversion rates increase approaching departure
 - Large parties have lower conversion rates that peak near departure

Different Types of Consumers: Frequent Fliers



- Frequent fliers arrive to purchase later with a higher overall conversion rate.

Estimation: Details

For each market $m \in \{1, \dots, 27\}$:

- 1 Estimate arrival process $\Lambda_m = \{\lambda_{mt}\}_{t=1}^T$ with search data
- 2 Solve model for fixed grid of $H = 1,500$ candidate DGPs
 - A candidate DGP is a vector of demand primitives $\psi = (\mu_\nu^L, \mu_\xi^L, \mu_\nu^B, \mu_\xi^B, \Delta_\gamma)$
- 3 Compute vector of aggregate market-specific moments \hat{g}_m from data and equivalent moments via simulation for each candidate DGP in matrix \tilde{G}_m
- 4 Estimate weights $\hat{\theta}_m$ of each DGP using constrained least squares:

$$\hat{\theta}_m = \arg \min_{\theta} (\hat{g}_m - \tilde{G}_m \theta)' (\hat{g}_m - \tilde{G}_m \theta)$$

$$\text{subject to } \sum_{h=1}^H \theta_h = 1 \text{ with } \theta_h \geq 0$$

Estimation: Visualization

$$\hat{\mathbf{g}} = \underbrace{\begin{bmatrix} \hat{g}_1 \\ \hat{g}_2 \\ \vdots \\ \hat{g}_{N_g} \end{bmatrix}}_{\text{Moments from data}} \quad \tilde{\mathbf{G}} = \underbrace{\begin{bmatrix} \tilde{G}_{11} & \tilde{G}_{12} & \cdots & \tilde{G}_{1H} \\ \tilde{G}_{21} & \tilde{G}_{22} & \cdots & \tilde{G}_{2H} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{G}_{N_g 1} & \tilde{G}_{N_g 2} & \cdots & \tilde{G}_{N_g H} \end{bmatrix}}_{\text{Columns are equivalent moments for each candidate DGP}} \quad \text{and } \boldsymbol{\theta} = \underbrace{\begin{bmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_H \end{bmatrix}}_{\text{Weight for each DGP}},$$

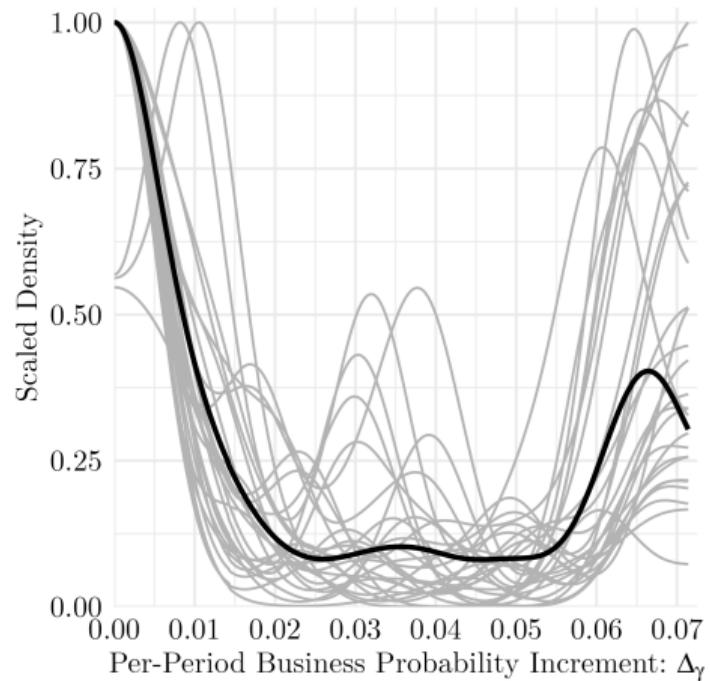
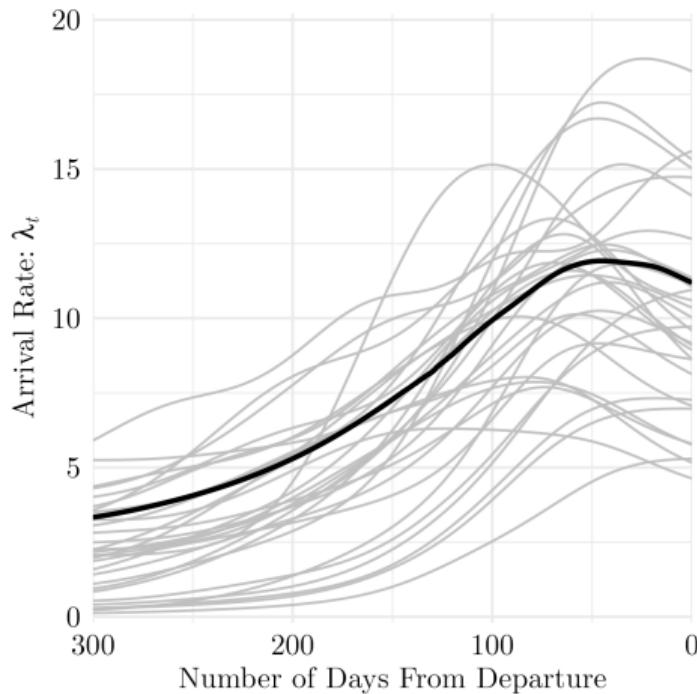
Solution minimizes squared differences between data and weighted average of candidate-DGP moments

$$\hat{\theta} = \arg \min_{\theta} \|\hat{g} - \tilde{G}\theta\|$$

$$\tilde{\mathbf{G}}\boldsymbol{\theta} = \theta_1\tilde{\mathbf{G}}_1 + \theta_2\tilde{\mathbf{G}}_2 + \cdots + \theta_H\tilde{\mathbf{G}}_H$$

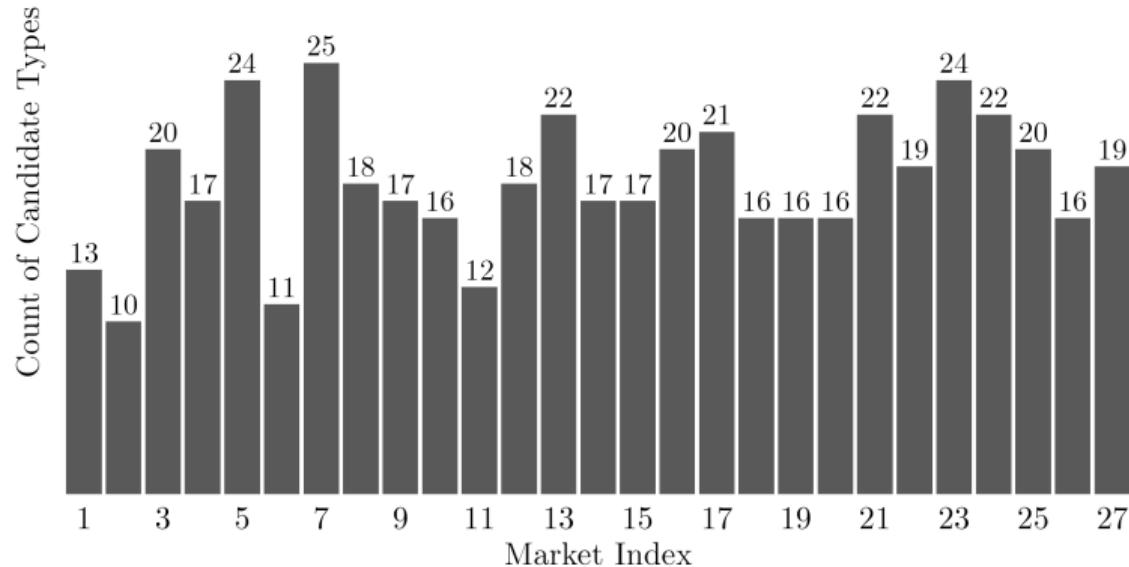
where $\tilde{\mathbf{G}}_k$ is the k^{th} column of $\tilde{\mathbf{G}}$.

Results: Arrival Process



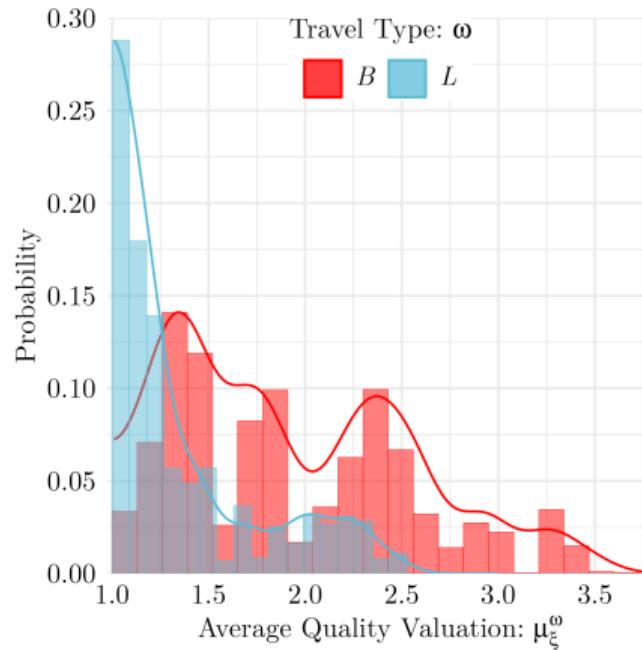
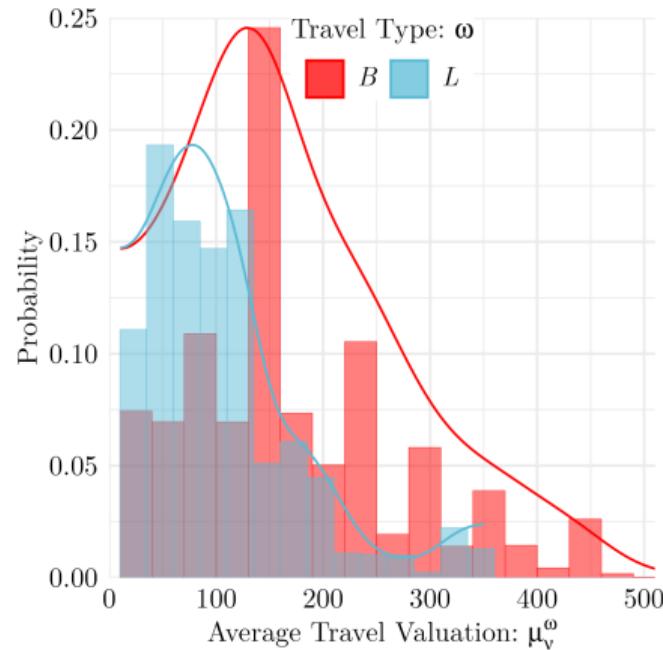
- Market-specific heterogeneity in number of arrivals and type probabilities

Results: Surviving Types



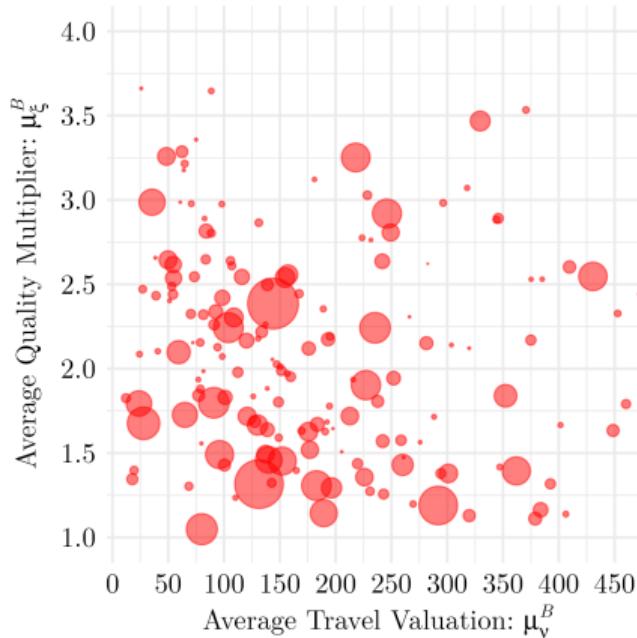
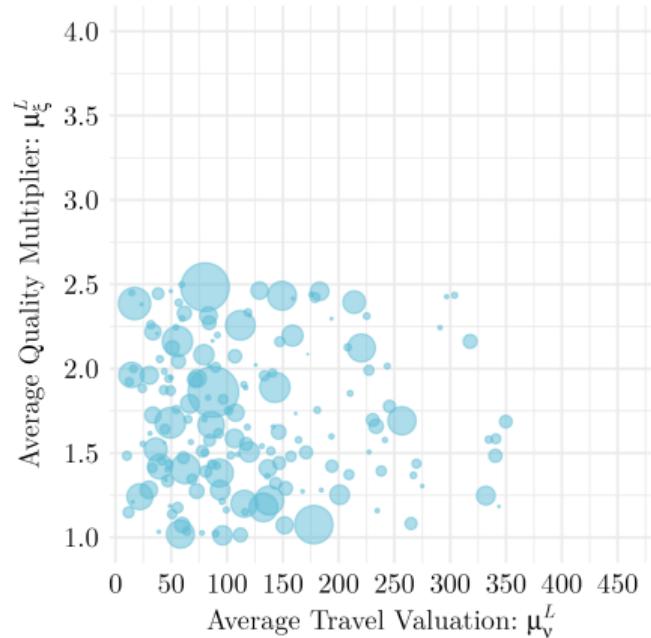
- Each market is described by few DGPs (i.e. 99.99% of the weight)
- Market-specific mixture captures heterogeneity across flights

Results: Consumer Heterogeneity - Marginal Distributions



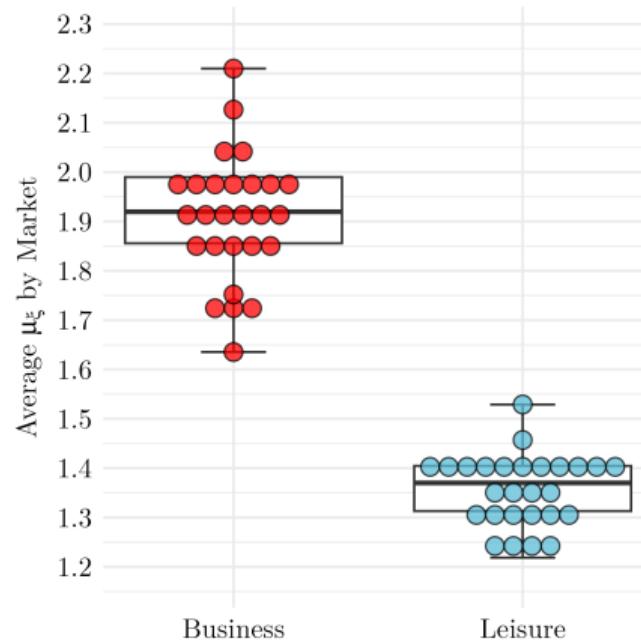
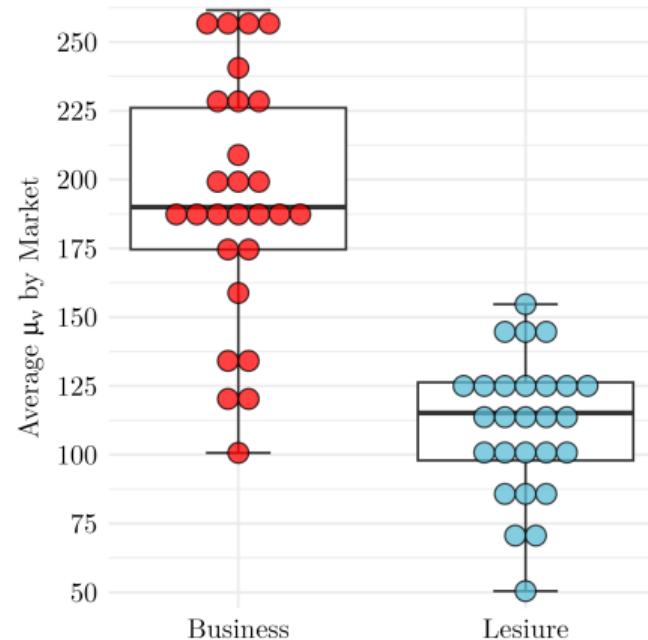
- Marginal distribution of air-travel and premium-cabin valuations aggregating across markets (business FOSD leisure)

Results: Consumer Heterogeneity - Joint Distributions



- Joint type-specific distribution of air-travel and premium-cabin valuations aggregating across markets (business more variable than leisure)

Results: Market Heterogeneity



- Distribution of market-specific mean of air-travel and premium-cabin valuations by consumer type (wide variety of preferences across markets)