Organizational Structure and Pricing:

Evidence from a Large U.S. Airline

Ali Hortaçsu, *University of Chicago and NBER*

Olivia R. Natan , *University of California, Berkeley*

Hayden Parsley, *Tobin Center for Economic Policy*

Timothy Schwieg, *Becker Friedman Institute*

Kevin R. Williams, *Yale School of Management and NBER*[*]

July 2021

Preliminary and Incomplete, Comments Welcome

Abstract

The availability of large amounts of data and improvements in computational technology have allowed firms to develop sophisticated pricing and allocation systems. However, decision rights within these systems are often allocated across different organizations/divisions within the firm. We study how organizational boundaries affect pricing decisions using comprehensive data provided by a large U.S. airline. Contrary to prevailing theories of the firm, we show that advanced pricing algorithms have multiple biases. These biases can be attributed to the various teams responsible for managing pricing algorithm inputs. To quantify the impacts of these biases, we estimate a structural demand model that combines sales and search information. We recover the demand curves the firm believes it faces using detailed forecasting data. In counterfactuals, we show that correcting biases introduced by teams individually have little impact on market outcomes, but addressing all biases simultaneously leads to higher prices and increased dead-weight loss in the markets studied. Our results suggest that decentralized decision making can curtail a firm's ability to set optimal prices.

---

[*]The views expressed herein are those of the authors and do not necessarily reflect the views of the National Bureau of Economic Research. 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. We also thank the seminar participants at Yale University, University of Virginia, Federal Reserve Bank of Minneapolis, University of Chicago, and University of California-Berkeley for comments. Emails: hortacsu@gmail.com, olivia.natan@berkeley.edu, timothyschwieg@uchicago.edu, hayden.parsley@yale.edu, kevin.williams@yale.edu

1 Introduction

Dramatic decreases in the cost of computation and data storage, along with algorithmic innovations, have increasingly allowed firms to develop data-driven decision optimization systems. Data and algorithms now play a key role in driving firm decisions across industries. This is especially true in the airline context where firms must match fixed flight capacity with dynamically evolving demand for hundreds or even thousands of flights a day. To solve this difficult allocation problem, sophisticated pricing systems have been developed over the last several decades.[1] These systems depend on inputs from multiple organizational teams that generate the sometimes mystifying patterns of prices customers are now accustomed to seeing. This type of organizational structure, and allocating decision rights across different divisions within the firm, is not unique to airlines. Hotels, cruises, car rentals, entertainment venues, and retailers have all adopted features of the airline pricing model. Given the investments firms have made into these sophisticated pricing systems and their wide use across industries, we may expect that prices are close to optimal.

In this paper, we study how organizational boundaries affect pricing decisions using by leveraging a data partnership with a large international air carrier based in the United States.[2] The granularity of the data allow us to understand the firm's incentives to adjust prices without needing to assume prices are optimally set. We show that, contrary to prevalent theories of the firm, the pricing at a sophisticated firm—one that employs advanced optimization techniques and has a heavy reliance on automation—does not appear to react to some important market fundamentals. This includes internalizing consumer substitution to other products, persistently biased forecasts, and not responding to changes in opportunity costs of remaining capacity driven by scarcity. We show that these biases are introduced by separate teams within the firm. What happens to prices and allocative efficiency if organizational teams addressed the persistent pricing biases that we document? Using a new technique to estimate demand and detailed forecasting data to infer the firm's beliefs

[1] See Talluri and Van Ryzin (2006) for a summary of this work.

[2] The airline has elected to remain anonymous.

about the demand it faces, we find that correcting pricing biases introduced by teams individually does little to affect market outcomes. The current pricing algorithm is effective at leaving few seats unsold. However, we also show that addressing all biases introduced across organizational teams can result in increased price targeting, higher revenues, but higher dead-weight loss for the routes studied. That is, pricing frictions introduced by decentralized decision making curtail the firm's ability to set optimal prices.

We begin by providing an empirical glimpse under the hood of dynamic pricing solutions used by airlines. In addition to observing prices and quantities, we also observe granular demand forecasts, output of the pricing and allocation algorithms, the optimization code itself, and clickstream data that detail all consumer interactions on the airline's website. The core data cover hundreds of thousands of flights spanning hundreds of domestic origin-destination pairs. Our structural analysis concentrates on routes in which the air carrier is the only airline offering nonstop service. We discuss the main organizational details of how pricing and seat allocation decisions are made within the organization and provide insights into how the data are used to understand the incentives to adjust prices over time in Section 2 and Section 3, respectively. We provide evidence that all major airlines have similar organizational structures and all use similar pricing algorithms. Therefore, we believe our discussion and subsequent empirical findings likely to hold for the industry broadly and perhaps to other industries that have adopted this pricing solution.

In Section 4, we discuss data patterns that suggest the airline could be doing more with its data. We show that prices are adjusted too infrequently compared to the output of the optimization algorithm that computes the shadow value or opportunity cost of each seat. Although this pricing rigidity is due to the discrete nature of "fare buckets" that are utilized by the industry, the variation in opportunity cost can sometimes extend several hundred dollars without triggering a price adjustment. This may suggest a mismatch between the fares chosen by one organizational team and demand fundamentals. We also establish that the airline responds to demand "surprises" too little and too late. Demand forecasts, maintained by a separate team, respond to demand surprises with delay. This leads to

missed opportunities both for the flight in question, but also for future flights which are mistakenly thought to be over-(or under-) demanded. We provide suggestive evidence that cross price elasticities are not considered when prices are set. For example, if the firm offers morning and evening flights, a demand shock for the morning flight does not impact the opportunity cost (nor the price) of selling a seat on the evening flight. Finally, we show that demand forecasts are persistently biased upward. Manager adjustments reduce the bias caused by the algorithms, but they are insufficient to fully deflate the forecasting bias in two years of data.

In the second stage of our analysis, we quantify the impact of these observed pricing frictions on welfare. To do this, we estimate a structural model of consumer demand using a recently proposed demand methodology (Hortaçsu, Natan, Parsley, Schwieg, and Williams, 2021). The approach allows us to estimate both preferences and aggregate demand uncertainty at granular levels, i.e., demand for a specific flight itinerary on a given day of sale.

In the model presented in Section 5, "leisure" and "business" travelers arrive according to independent and time-varying Poisson distributions in discrete time. Consumers know their preferences and solve discrete choice maximization problems. Each arriving consumer chooses among the available flight options or an outside option. We provide evidence to motivate our demand assumptions, including that consumers do not appear to be betting on price, consumer arrivals are not endogenous to price, and that booking patterns are similar if consumers purchase through online travel agencies, e.g., Expedia.com. The model allows for a rich set of demand covariates and an additional flight-level demand unobservable which is correlated with price. On occasions where flights are observed to sell out, we consider censored demand.

We estimate the model using consumer search and bookings data. Aggregate search counts calculated from the clickstream data inform the overall arrival process, whereas we identify the price coefficient using instrumental variables (see Section 6). In order to keep our analysis manageable, we estimate demand for 40 markets that best allow us to control

for features outside the model, including competition and connecting traffic. The estimates presented in Section 7 reveal meaningful variation in demand, with a general increase in search for travel as the departure date approaches and substantial changes in the overall price sensitivity of consumers over time. Across routes, we find substantial heterogeneity in arrivals, pricing patterns, and consumer responses to prices. Typically, leisure-favored routes are more price sensitive, while business-heavy markets show more heterogeneity between consumer types.

Given the demand estimates, we then ask: what does the firm believe its demand curves look like? We call these "firm beliefs" and we recover them in Section 8. Using output from an algorithm that classifies search behavior as coming from a "leisure" passenger or a "business passenger," we recalbirate our estimated arrival rates. Next, we infer the firm's beliefs on consumer preferences by matching the demand model to repeated cross sections of the firm's granular forecasting data. Because the forecasting data are at the consumer-type level, we can use the inversion of Berry (1994) and Berry, Levinsohn, and Pakes (1995) to recover preferences on all product characteristics. Relative to our baseline demand estimates, we show that demand recovered using the forecasting data yield more compressed elasticities both within and across routes, more elastic demand near departure, and consumer types that are "closer together" in terms of preferences.

We use the recovered beliefs and the demand estimates to quantify market outcomes of the pricing frictions that we have identified in Section 9. Our model of pricing closely follows the pricing algorithm the firm actually uses. First, we isolate pricing frictions individually. What happens if the firm uses a demand forecast that is not biased but holds other inputs fixed? What happens if the firm specifies alternative fares that more closely assign to willingness to pay but holds other inputs fixed? We show that outcomes are largely unchanged. That is, correcting pricing frictions individually does not lead to significant welfare changes as the decisions by the pricing algorithm are largely unchanged. However, we also show that adjusting the organizational structure of the firm to provide feedback across teams can lead to very different outcomes. We consider this scenario by correcting

the forecast and inputting fares into the algorithm tailored to this forecast. Outcomes are very different as the firm can better target late-arriving consumers with higher prices. This in return affects all consumers because the opportunity costs of capacity rise. Revenues increase substantially—upward of 20% for some markets—at the expense of all consumers. We find dead-weight loss increases by over 10%. The fact that that the firm could extract additional surplus but has chosen not to do so is puzzling. We argue that this is possible due to under-experimentation across organizational teams that we quantify in the data. We also hypothesize the firm may consider the implicit cost of regulatory oversight or long-term competitive responses as alternative explanations.

1.1 Related Literature

This paper contributes to research in behavioral and empirical industrial organization, organizational economics, and operations research.

Recent research has documented pricing frictions in several industries, including DellaVigna and Gentzkow (2019) and Hitsch, Hortaçsu, and Lin (2019) in retailing, Huang (2021) in peer-to-peer markets, Ellison, Snyder, and Zhang (2018) in online retailing, and Cho and Rust (2010) in rental cars. One main finding across these papers is the infrequency of adjustment or the uniformity of prices across markets and time. We confirm pricing frictions also impact firms that have adopted sophisticated pricing algorithms. Our work contributes to research on miscalibrated firm expectations (Massey and Thaler, 2006; Akepanidtaworn, Di Mascio, Imas, and Schmidt, 2019; Ma, Ropele, Sraer, and Thesmar, 2020).[3][4] Dubé and Misra (2021) provide an example where a firm has chosen a uniform price substantially lower than optimal. We find if the firm prices according to the correct demand curve, outcomes are largely unchanged due to the presence of other pricing biases.[5]

[3]See Aguirregabiria and Jeon (2020) and DellaVigna (2018) for a summary of work in behavioral industrial organization.

[4]Although we cannot link our results to managerial ability, as in Goldfarb and Xiao (2011) and Goldfarb and Xiao (2016), we do show that observed managerial adjustments to inputs "go the correct way." That is, managers work to debias algorithms. These adjustments are insufficient to fully debias algorithms in two years of data.

[5]Our work also complements studies that investigate the welfare effects of dynamic pricing, e.g., Sweeting

We also contribute to the literature in organizational economics. An influential literature studying the productivity effects of information technology (IT) suggests that IT adoption works best if complementary organizational and management practices are implemented alongside these investments—for example, Bresnahan, Brynjolfsson, and Hitt (2002) and Bloom, Sadun, and Van Reenen (2012)).[6] Although Athey and Stern (2002) do not find strong complementarities in an IT setting, we find substantial complementarities in the context of pricing algorithms.[7] There also exists a substantial theoretical literature that analyzes teams, complementarities, and organizational structure, including Che and Yoo (2001), Siemsen, Balasubramanian, and Roth (2007), Alonso, Dessein, and Matouschek (2008, 2015). Our paper is a detailed case study that quantifies the importance of coordination across complementary inputs to firm decisions.

Finally, this paper quantifies the effectiveness of pricing heuristics proposed in operations research using airline data (Littlewood, 1972; Belobaba, 1987, 1989; Brumelle, McGill, Oum, Sawaki, and Tretheway, 1990; Belobaba, 1992; Wollmer, 1992).

2 Organizational Structure and Division Responsibilities

We study the US airline industry, an industry that directly supports over two million jobs and contributes over $700 billion to the US economy.[8] In 2019 alone, 811 million passengers flew within the United States.[9]. In addition to being an important industry in its own right, airlines have been influential in the development of pricing technologies that are now used in other sectors—for example, in hospitality, retailing, and entertainment and sports events. Although the sophistication of these technologies has improved, much of the core

(2012); Cho, Lee, Rust, and Yu (2018); Hendel and Nevo (2013); D'Haultfœuille, Février, Wang, and Wilner (2019); Castillo (2019); Lazarev (2013); Aryal, Murry, and Williams (2018), and Williams (2021).

[6]See Brynjolfsson and Milgrom (2012) for an overview of this work

[7]Studies have also examined the impacts of human resource practices and performance (e.g., Ichniowski, Shaw, and Prennushi (1997)).

[8]Source: https://www.iata.org/en/iata-repository/publications/economic-reports/the-united-states–value-of-aviation/, accessed July 1, 2021.

[9]Source: https://www.bts.gov/newsroom/2019-traffic-data-us-airlines-and-foreign-airlines-us-flights-final-full-year, accessed July 1, 2021.

responsibilities and methods described in McGill and Van Ryzin (1999) remain in place today.[10]

In this paper, we study the pricing decisions of a single airline. This affects some of our choices—for example, which markets to study—however, our institutional setting is representative of how all airlines operate (see Section 2.1).

Fares offered to travelers depend on the actions of manager in several distinct departments. Generally, decisions become increasingly granular, taking all previous departments' decisions as given. First, network planning decides the network, flight frequencies, and capacity choices. In this paper, we do not endogenize these actions. Second, the pricing department sets a menu of fares and fare restrictions for all possible itineraries. These are potential prices consumers may face. Finally, the revenue management (RM) department decides the number of seats to sell (at each price and point in time). In this paper, we consider the impacts of these two critical inputs on the effectiveness of the pricing algorithm.

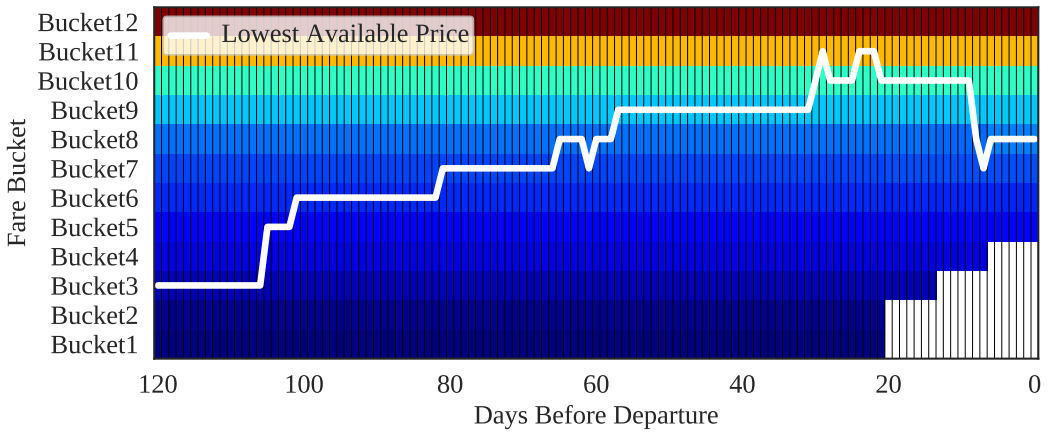
RM has decision rights to the forecasting model and the pricing algorithm. The forecasting model incorporates historical information and current bookings information to predict flight-level sales. The pricing algorithm allocates remaining inventory to the set of fares assigned by the pricing department.[11] The algorithm itself is a heuristic developers by academics in operations research. A commonly used heuristic is Expected Marginal Seat Revenue (EMSR), which closely approximates the algorithm used by the firm. We provide additional details of the EMSR in Appendix A and outline the algorithm here. EMSR belongs to a class of static optimization solutions. Dynamics are removed because it assumes all future demand will arrive tomorrow. The key trade-off is to offer seats today versus reserve them for future demand. Given inputs, it calculates the opportunity cost of a seat

[10]Interested readers can find additional insights in Talluri and Van Ryzin (2005).

[11]Each filed fare contains an origin, destination, filing date, class of service, routing requirements, and other ticket restrictions. Filed fares may also have an expiration date that cause another fare to become active after this date. However, the pricing department may file updated fares at any point in time. It is common that filed fares affect all (or at least most) departure dates simultaneously. A common ticket restriction is an advance purchase discount, which specifies an expiration date for a discounted fare to be purchased by. These discounts are commonly observed seven, 14, and 21 days before departure. Several others exist as well. This includes, 1, 2, 30, 45, and 60 day AP requirements.

and then assigns the number of seats it is willing to sell at all price levels. Lowest priced units are assumed to sell first. If expected future demand is high, it will restrict inventory at lower prices today. If expected future demand can be satisfied with current capacity, it will allocate more seats to lower fares today.

Figure 1: Fare Bucket Availability and Lowest Available Fare



Note: Image plot of fare availability over time as well as the active lowest available fare. Bucket1 is the least expensive; Bucket12 is the most expensive fare class. The color depicts the magnitude of prices—blue are lower fares, red are more expensive. White space denotes no fare availability. The white line depicts the lowest available fare.

Figure 1 depicts output from the decisions of both pricing and RM. The horizontal axis marks days before departure. On the vertical axis, we show the anonymized fare buckets, with bucket one being the least expensive and bucket twelve being the most expensive. The price level chosen by the pricing department is shown from blue (low) to red (high). Fare availability, also chosen by the pricing department, is shown in white. The bottom right of the graph shows the lowest fares cannot be offered close to the departure date. Given fares and the forecast, the white line marks to lowest available price (LAP) offered to consumers. This is an output of the algorithm. Not shown in the graph is the number of seats allocated to LAP. Price dispersion within a period can happen if all seats at LAP sell. The price will then increase to the next bucket with availability.

2.1 Pricing Practices Across US Airlines

We collect job postings information from all the major air carriers in the United States to confirm that all carriers use the organizational structure just described, with three departments influencing flight prices. Table 1 shows all US airlines have a network planning, pricing, and revenue management department.

Table 1: Department Presence by Airline

Airline	Network Planning	Pricing Department	Revenue Management
Alaska	✓	✓	✓
American	✓	✓	✓
Delta	✓	✓	✓
JetBlue	✓	✓	✓
Southwest	✓	✓	✓
United	✓	✓	✓

As an example, JetBlue Airlines job postings show that the firm has three teams related to pricing: Future Schedules, Revenue Management-Pricing, and Revenue Management-Inventory. Job details delineate team responsibilities. The network planning group (called Future Schedules) is "responsible for building JetBlues strategic schedule plans for the route network >3 months prior to operating", and analysts are specifically tasked with maintaining the flight schedule 330 to 90 days before departure.[12] The Revenue Management department at JetBlue has two separate teams, Pricing and Inventory. The Pricing teams maintain the fare schedule by "monitoring industry pricing changes filed through a clearinghouse throughout the day, and determining and executing JetBlues response."[13] The Inventory team performs the last step of revenue management we describe above by using "inventory controls to determine the optimal fare to sell at any given moment in time to maximize each flights revenue."[14] Each department's job posting acknowledges the po-

[12] Source: https://careers.jetblue.com/job/Long-Island-City-Senior-Analyst-Schedule-Planning-NY-11101/759889600/, accessed July 1, 2021

[13] Source: https://careers.jetblue.com/job/Long-Island-City-Analyst-Revenue-Management-NY-11101/737962800/ accessed July 1, 2021.

[14] Source: https://careers.jetblue.com/job/Long-Island-City-Analyst-Revenue-Management-NY-11101/737962800/ accessed July 1, 2021.

tential spillovers between groups but separately outlines these demand-relevant decisions as being conducted separately. Because all carriers have the same organizational structure, we believe our analysis appropriately characterizes the entire industry, rather than the perspective from a single firm.

3 Data Introduction

We use novel and comprehensive data provided by a large international air carrier based in the United States. To maintain anonymity, we exclude some details on the markets studied and report some statistics using normalizations. Online Appendix B provides details on how we selected the hundreds of routes used in this study. We derive our descriptive evidence from a diverse set of routes. Our structural analysis concentrates on routes in which our airline is the sole airline offering nonstop service. Additional details on the construction and cleaning of the data can be found in Online Appendix **??**.

3.1 Data Tables

We combine several data sources, which we commonly refer to as: (1) bookings, (2) inventory, (3) search, (4) fares, and (5) forecasting data. We provide an overview of these tables before providing descriptive evidence.

(1) Bookings data: The bookings data contain details for each purchased ticket, regardless of booking channel (e.g., the airline's website, travel agency, etc.). Key variables included in these data are the fare paid, the number of passengers involved, the particular flights included in the itinerary, the booking channel, and the purchase date.[15] The airline uses an algorithm to infer the types of passengers involved in every search and booking. Over 90% of interactions are assigned to be either "leisure" or "business" traveler. Therefore, we concentrate on these two types.[16] Our analysis concentrates on nonstop bookings

[15] We document facts using nonstop bookings, however, our measure of remaining capacity adjusts for all tickets sold (e.g., connections, reward tickets, and consumers altering tickets, etc.).

[16] We reclassify the other categories as leisure.

and economy class tickets.

(2) Inventory data: The inventory data contain the decisions made by RM. Inventory allocation is conducted daily. The data include the number of seats the airline is willing to sell for each fare class in economy. We also observe output from the pricing algorithm, including the opportunity cost of a seat.

(3) Search data: We observe all consumer interactions on the airline's website. The clickstream data include search actions, bookings, and referrals from other websites. Tracking occurs regardless as to whether an individual has a consumer loyalty account and is logged in. Consumers can be linked across cookies. For this project, we aggregate search activity to the level of origin-destination-booking date-departure date. Additional details, including how we adjust for the number passengers involved, how we adjust for search activity across multiple departure dates, etc., can be found in Online Appendix **??**.

(4) Filed fares data: The filed fares data contain the decisions made by the airline's pricing department, as described in Section 2. We observe all filed fares for over half of our sample. A file fare contains the price, fare class, and all ticket restrictions, including any advance purchase discount requirements.

(5) Forecasting data: The air carrier forecasts future demand at granular levels. We observe these predictions down to the flight-passenger type-price level. In addition to the baseline forecast, we also observe all managerial adjustments to the algorithms. These adjustments may occur because managers believe demand will be higher or lower than originally planned. We observe these detailed forecasts for a subsample of booking dates.

3.2 Data Summary

Table 2 provides a basic summary of the nearly 300,000 flights in our cleaned sample. We focus in the last 120 days before departure due to the overwhelming sparsity of search and sales observations earlier in the booking horizon.

Average flight fares in our sample are $194, with large dispersion across markets and over time. Typically, prices for a particular flight adjust nine times and double in 120

Table 2: Summary Statistics

Data Series	Variable	Mean	Std. Dev.	Median	5th pctile	95th pctile
Fares						
	One-Way Fare ($)	173.9	129.7	138.5	68.5	369.0
	Num. Fare Changes	9.3	4.2	9.0	3.0	17.0
	Fare Changes | Inc.	46.9	67.9	29.0	2.0	153.0
	Fare Changes | Dec.	-49.3	70.2	-30.0	-163.0	-4.0
Bookings						
	Booking Rate-OD	0.2	0.7	0.0	0.0	1.0
	Booking Rate-All	0.6	1.4	0.0	0.0	3.0
	Load Factor (%)	82.2	21.4	90.0	36.0	102.0
Searches						
	Search Rate	1.7	4.2	0.0	0.0	8.0

Summary statistics for the data sample. Fares are for nonstop flights only. The initial load factor is the percentage of the number of seats occupied 120 days before departure. The booking rate is for nonstop flights. The number of passengers denotes the number of passengers per booking. The ending load factor includes all bookings, including award and connecting itineraries. The search rate is for origin-destination queries at the daily level. The number of passengers is the number of passengers per request.

days. Many adjustments occur at specified times—after expiration of advance purchase discounts. However, over 60% of price adjustments occur before the first AP fares expires. This is because inventory (and therefore, prices) is re-optimized daily.

The average booking rate for nonstop itineraries is 0.2. The 5th percentile is zero and the 95th percentile is one. Inclusive of connecting itineraries (Booking Rate-All), rates are still low (0.2). Airline demand is low at granular (daily) levels. Table 2 establishes that search volume on the airline's website is also low, at less than two searches per day.[17] Ending load factor reports the percentage of seats occupied on the departure date. The mean is 82.2% and the median is 90.0%.[18] The 95th percentile is above 100% meaning more than 5% of flights have total bookings at or above capacity on the day of departure. We do not model overselling in this paper because we do not observe actual enplanements (individuals who purchased and were denied boarding).

[17]This is at the origin-destination-departure date-search date level.

[18]The initial load factor reports the percentage of seats occupied 120 days before departure. The average is 8.3% and the median is less than 4.7%.

3.3 Empirical Facts that Motivate Demand Assumptions

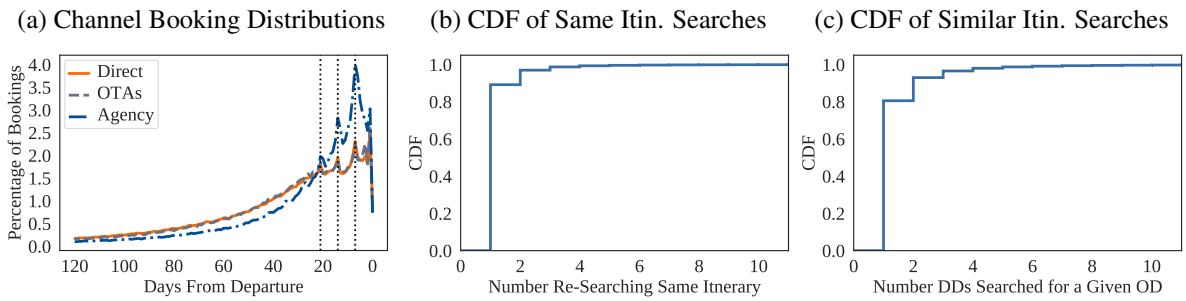
We use our novel data to motivate some of our demand assumptions. Figure 2-(a) motivates our assumption on scaling consumer search observed on the airline's website. It plots the within bookings channel distribution of sales over time. OTAs, or online travel agencies, closely follows the distribution of bookings via the direct channel. This means consumers shopping on platforms, such as Expedia.com, may not be very different from the consumers who purchase tickets directly with the airline. Indeed, the distribution of purchases nearly coincide. The agency curve, which includes corporate travel partners, is more concentrated close to departure when fares tend to be higher. This motivates an adjustment to our demand model where we will account for unobserved consumer search activity differently across time. Our core assumption will be that search and sales behavior on airline's website is representative of all search and sales behavior, but the fraction of all observed searches changes over time.[19]

Figure 2-(b) and (c) motivate our assumption that consumers solve a static optimization problem. We investigate the tendency for consumers to return to search for tickets.[20] Panel (c) shows the cdf of number of times that consumers search for the same itinerary across days. 90% of consumers search for an itinerary (OD-DD pair) once. Conditional on consumers searching more than once, the average number of days between searches is 9.9 days, and the median is 4.0 days. Panel (d) shows the cdf for the number of different departure dates (for the same OD) that consumers search for. 82% of customers search a single departure date. The average time lag between searches is 45 days, and the median is

[19]Figure 2-(a) shows that the booking distributions are not smooth, with small dips after advance purchase fares expire. We acknowledge that consumers may expect fares to rise and purchase before fare hikes, however, this actually occurs regardless as to whether a fare hike would actually take place. To establish this, we investigate consumers' search activity. We split the sample into two groups, one that includes markets that never have 7-day AP requirements, and one that includes markets that do have 7-day AP requirements. We can show that that search activity (and purchases) bunch at the 7-day AP requirement, regardless as to whether they exist. Perhaps some consumers have been trained to avoid booking on certain days. Because there is an increase in search activity, regardless of price adjustments, we believe this is captured through an arrival rate parameter for each day before departure, irrespective of price. That is, search is endogenous to time but not endogenous to price.

[20]For this analysis, we exclude searches who were referred to the airline from other flight search websites, e.g., Kayak, Google Flights, etc.

Figure 2: Search and Booking Facts to Motivate Demand Model



(a) Percentage of Bookings, across days from departure, for each Channel. Direct refers to bookings that occur on the air carrier's website, OTAs is purchases made on online travel agencies, and Agency are bookings made through travel agencies. (c) Empirical CDF of the number of days from departure searchers appear for a given itnerary. (d) Empirical CDF of the number of departure dates a given searcher looks for.

12 days. Of the consumers who search for more than one departure date, most do not look at the same departure date more than once. Our general impression of the clickstream data is that some consumers may not be certain about their travel plans (however, such a large mass of repeat shoppers of different departure dates have several months between searches that this may suggest entirely different purchasing opportunities), but there is little evidence of consumers continue to search for the same itinerary as the departure date approaches.

The bookings data suggest unit demand is a reasonable assumption. The average passengers per booking is 1.3. As described in Section 2, airlines typically offer several different fare classes at any point in some. These tickets may have different features, such as refundability; sometimes different fare classes have identical restrictions. We use data on all transactions and compare the price paid to the lowest economy class fare offered on that day. In our data, 91% of consumers purchase the lowest available fare which motivates our choice of assuming all consumers select to pay the lowest available fare for a given flight.

The data highlight how sparse bookings and searches (before scaling, but also true after scaling) are. 60-80% of observations contain zero searches across our 400 markets. The fraction of zero sales is even higher, where most routes have more than 80% zeros. Zeros are not just present because we investigate nonstop demand. The fraction of zero sales for any itinerary is between 40-80% for any itinerary. As previously stated, the search rate

is less than two on average. This mean is driven upward by searches close to departure. For a majority of booking dates, searches are less than one. This makes Poisson the ideal distribution to model search counts, and we capture variation in the search rate with time-specific parameters.

Finally, in our market-level demand system, we will assume all consumers pay the same price. This is overwhelmingly true in the data (almost a given since purchases are infrequent and the median number of passengers per booking is one).

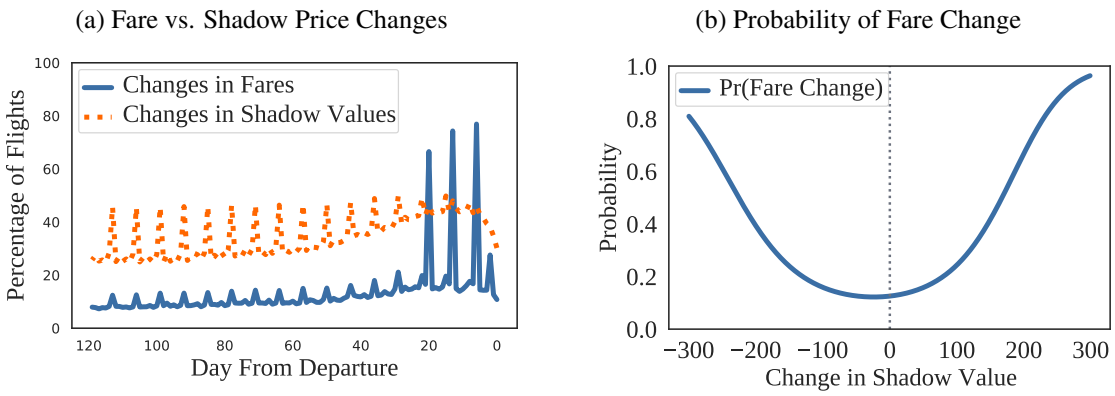
4 Pricing Frictions Due to Decisions of Different Divisions

In this section, we document that the firm does not price optimally. This is due in part because the inputs into the pricing algorithm are “incompatible" in the sense that they prohibit revenue maximization. Specifically, we show that pricing does not respond to all available information (Section 4.1), does not internalize cross-product substitution (Section 4.2), and utilizes persistently biased demand forecasts (Section 4.3). We attribute each bias to the team responsible for its input.

4.1 Not Responding to All Available Information

Figure 3 demonstrates that the firm has access to, and indeed generates, payoff relevant information that its pricing algorithms do not seem to respond to. In panel (a), we plot the fraction of flights that experience changes in price or marginal costs (the shadow value on the capacity constraint) over time. The figure shows that costs change at a much higher frequency than do prices. This occurs because of the industry practice of using fare buckets—it is possible than marginal costs change by $1, but the next fare is $20 more expensive. Our analysis suggests this friction is significantly more important. In panel (b), we run a flexible regression of the change in costs on an indicator function for a price adjustment occurring. As the figure shows, changes in marginal costs exceeding $150 are addressed with the odds of a coin flip. This may suggest that revenues could be higher if the pricing

Figure 3: Fare Adjustments in Response to Opportunity Cost Changes



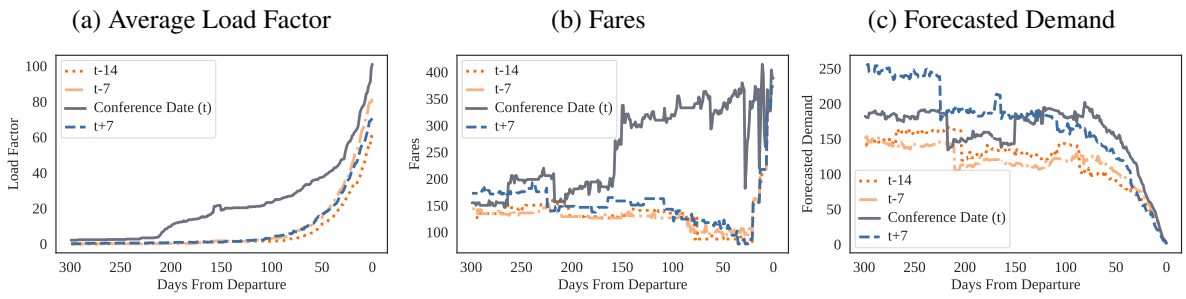
Note: (a) The fraction of flights that experience changes in the fare or the opportunity cost of capacity over time. (b) The probability of a fare change, conditional on the magnitude in the change in the shadow value.

department filed alternative fares that better match demand and capacity limitations across markets. Panel (a) also shows instances where prices adjust but the opportunity cost of a seat has not changed.

Note the spikes in Figure 3-(a). These spikes occur at seven day intervals because that is when the firm reforecasts demand for future flights. Outside of these periods, the firm simply reoptimizes inventory given the forecast. This is perhaps another pricing friction in that RM has chosen to not update forecasts continuously. We demonstrate via an example that information exists which could improve/tune forecasting models. With the current system, reactions to "surprises" occur too little and too late. In particular, demand forecasts maintained by RM respond to demand surprises with delay, leading to missed opportunities both for the flight in question, but also for future flights which are mistakenly thought to be over-(or under-) demanded.

In Figure 4, we show the average load factor, forecasted demand, and average fares for a conference which alternates both date and location each year. In addition to the conference date represented as the grey line, we include information for one week before and after the conference date for comparison. As shown in panel (a), as soon as the location and date of the conference is announced, around 200 days from departure, there is a sudden

Figure 4: Reacting to Surprises: A Conference Example



Note: All plots contain data series for flights departing the date of a large conference (which moves both location and dates each year) and the corresponding flights in the surrounding weeks of the conference. (a) Shows the average load factor across flights (b) Contains the average lowest available fares across flights (c) Has the average total expected seats to sell at a given point in time unconstrained by the remaining capacity.

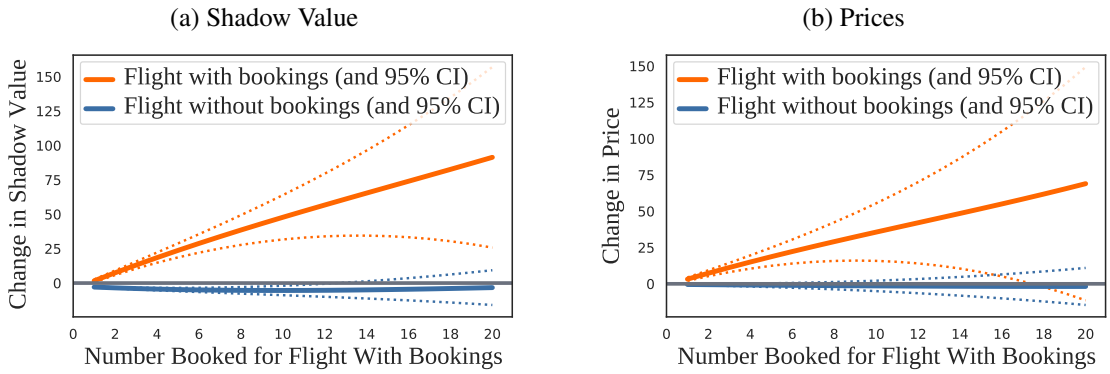
jump in the load factor. The firm's revenue management software responds with delay (over a month) to the sudden jump in bookings. Prices eventually increase dramatically as seen in panel (b). In panel (c), we plot forecasted demand remaining. The forecasting algorithm observes the conference shock and reevaluates demand for alternative departure dates. The forecast for flights a week later increases (to higher levels than the conference flights early on). However, in panel (a), we see that the flights a week later observes no surprises—bookings follow a similar pattern as other dates. Consequently, fares are too high for the non-conference flights and too low for a conference flights. The search data (not shown) establish that the conference date flights have abnormal search behavior and the flights a week later actually have lower search volumes than all the dates shown. It may be cost prohibitive to adjust forecasts daily, but this additional information could increase revenues.

4.2 Not Accounting for Cross-Price Elasticities

Dynamic pricing is computationally and theoretically complicated. Research in operations research have offered heuristics to solve such models, but this typically comes at the cost of abstracting away from key market forces. We show one important market feature not captured in the algorithm maintained by RM are cross-price elasticities.

To show that pricing does not internalize substitutes, we subsample our data. We extract observations that satisfy the following conditions: (1) the firm offers two flights a day; (2) we include periods where demand is not being reforecasted (theobserved as spikes in Figure 3); (3) the total daily booking rate is low (less than 0.5); and (4) one flight receives bookings and the other flight does not. It is important that we exclude periods in which the firm is learning about demand. By considering markets where the total booking rate is low, the following intuition uses theoretical results in continuous time.

Figure 5: Shadow Value and Price Response to Bookings with Multiple Flights



Note: (a) The orange line denotes the average change in shadow value for a flight when a sale at a given intensity occurs. The blue line is the average change to shadow value when a sale occurs to another flight at a given intensity. (b) This panel depicts the same as panel a, but instead of changes in shadow value it depicts changes in price.

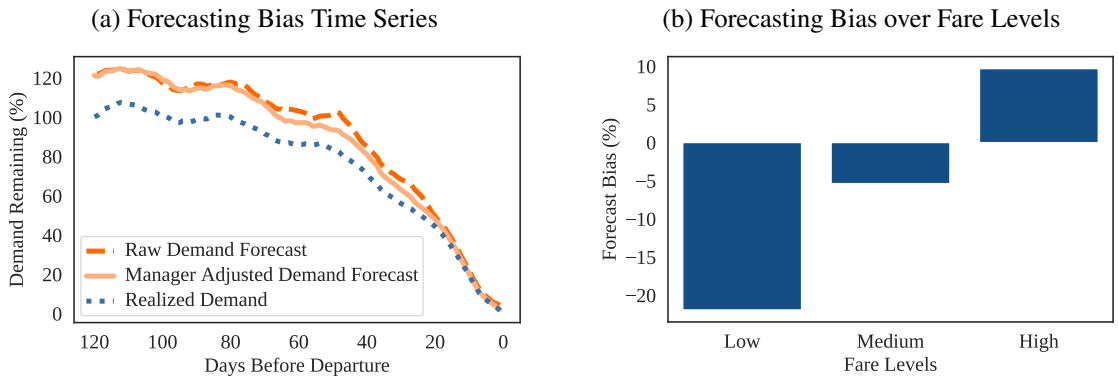
In Figure 5-(a), we plot the average change in shadow values for the flights that receive bookings and for the flights that do not receive bookings (the substitute option) using a flexible regression (orange for the flight with bookings; blue for the flight without bookings). In standard continuous time dynamic pricing models, every time a unit of capacity is sold, prices jump—every sale is a "surprise" (see, for example, Gallego and Van Ryzin (1994)). This is also true in dynamic models with multiple products: any capacity decrease causes all substitute prices to increase. Figure 5 shows this is not the case in the airline context. For example, if one flight has five bookings, the shadow value for that flight increases by over $25, but the shadow value for the substitute flight leaving on the same day is unchanged. Figure 5-(b) confirms the same is true when looking at price responses.

4.3 Persistently Biased Forecasts

Recall that we have data on the firm's demand forecasts at the flight-passenger-type-price level, along with manual adjustments to these forecasts. We find that the forecasting model maintained by RM systematically overstates future demand, and the bias is persistent in two years of data.

In Figure 6, we plot the firms' forecast against realized future sales. On average, the firm's forecasts are biased upwards from the true distribution of future sales for nearly the entire booking horizon. For the median observed forecast, the forecast is 10% higher than the actual future demand, which is equivalent to predicting an extra 2.5 seats will be sold. The forecast is closer to mean-zero only in the selling period just before departure. This bias is present in both the business and leisure passenger-type forecasts. In addition to the bias in the overall magnitude of future sales, the forecasting model also misses the realized distribution fares transacted (panel b). Across all of our markets, low-fare transactions are underforecasted by 20%, and high-fare transactions are overforecasted by 10%. This suggests the forecasting model does not accurately predict the composition of demand correctly.

Figure 6: Firm Forecasting and Realized Sales



Note: Forecasts and future sales are normalized by the aircraft's total coach capacity. Plots show 7-day moving average to smooth across strong day of week effects in the forecast sample. (a) Business traveler forecasts and realized sales. (b) Leisure traveler forecasts and realized sales.

In Figure 6-(a), we include both the raw forecast as well as the forecast after user adjust-

ments. We find that user adjustments improve the forecast accuracy, but the improvement is small in magnitude relative to the total bias. Because the forecasting model is just a single input, it is unclear that a mean zero forecast is optimal. For example, if the distribution of filed fares from the pricing department are "too low" relative to demand and scarcity, the best thing RM could do to the forecasting model is artificially inflate it. This will raise opportunity costs and increase fares. We explore these ideas in counterfactuals.

5 Empirical Model of Air Travel Demand

In order to quantify the impacts of the pricing biases just discussed, we need to estimate a model of air travel demand. We utilize both the demand model and estimation approach of Hortaçsu, Natan, Parsley, Schwieg, and Williams (2021). Here, we provide an overview of the model.[21]

We consider the demand for flights for a particular origin-destination pair departing on a particular departure date. We focus on consumers booking nonstop itineraries from a single air carrier and abstract from potential correlations in demand across alternative connecting flight options and alternative departure dates. Time is discrete. The definition of a market is an origin-destination (r), departure date (d), and day before departure (t) tuple. The booking horizon for each flight j leaving on date d is $t \in \{0, ..., T\}$. The first period of sale is $t = 0$, and the flight departs at T. In each of the sequential markets t, we assume all consumers face a single price for each flight j as within-day price changes are rare. Flights are imperfect substitutes, and we allow for product-specific preferences. Consumers solve a discrete choice utility maximization problem. Arriving consumers choose the flights from a choice set $J(r, t, d)$ that maximize their individual utilities, or select the outside option. We denote this option by $j = 0$. We assume the firm does not oversell as this also occurs rarely in the data.

Based on limited across-market search shown in Section 3.3, we assume arriving con-

[21] See Hortaçsu, Natan, Parsley, Schwieg, and Williams (2021) for details.

sumers do not substitute across alternative departure dates d' or wait to purchase on an alternative day before departure t'. For notational parsimony, we suppress the r subscript in the notation; all parameters are origin-destination specific.

Finite capacity and discrete time means that demand may exceed remaining capacity for any flight offered. We incorporate two assumptions that greatly simplify the demand system. Note that these assumptions are only binding in the period in which a flight actually sells out, which the data show happens rarely. Denote $C_{j,t,d}$ to be the remaining capacity. First, we assume that consumers are not forward looking and do not strategically choose flights based on remaining capacity, $C_{j,t,d}$. We avoid the complication that consumers may choose a less preferred option in order to increase the chances of securing a seat. Second, we assume that when demand exceeds remaining capacity for a particular flight, consumers who chose that flight are randomly shuffled; the first $C_{j,t,d}$ are selected, and the rest receive the outside option.

5.1 Utility Specification

Arriving consumers are one of two types, corresponding to leisure (L) travelers and business (B) travelers. An individual consumer is denoted as i and her consumer type is denoted by $\ell \in \{B, L\}$. The probability that an arriving consumer is a business traveler is equal to γ_t.

We assume the indirect utilities are linear in product characteristics and given by

$$u_{i,j,t,d} = \begin{cases} X_{j,t,d}\beta - p_{j,t,d}\alpha_{\ell(i)} + \xi_{j,t,d} + \varepsilon_{i,j,t,d}, & j \in J(t,d) \\ \varepsilon_{i,0,t,d}, & j = 0 \end{cases}.$$

In the specification, $X_{j,t,d}$ denote product characteristics other than price $p_{j,t,d}$. Consumer preferences over product characteristics and price are denoted by $\left(\beta, \alpha_\ell\right)_{\ell \in \{B,L\}}$. For notational parsimony, we commonly refer to the collection $\{\alpha_B, \alpha_L\}$ as α. For our empirical application, we isolate consumer heterogeneity in preferences to be on price. The term

$\xi_{j,t,d}$ denotes an unobserved (to the econometrician) product quality that is allowed to be correlated with price. The interpretation of $\xi_{j,t,d}$ is similar to previous demand estimation methodologies (Berry, 1994; Berry, Levinsohn, and Pakes, 1995). The term $\varepsilon_{i,j,t,d}$ is an unobserved random component of utility and is assumed to be distributed according to a type-1 extreme value distribution. All consumers solve a straightforward utility maximization problem; consumer i chooses flight j if, and only if,

$$u_{i,j,t,d} \geq u_{i,j',d,t}, \forall\, j' \in J \cup \{0\}.$$

The distributional assumption on the idiosyncratic error term leads to analytical expressions for the individual choice probabilities of consumers (Berry, Carnall, and Spiller, 2006). In particular, the probability that consumer i wants to purchase a ticket on flight j is equal to

$$s^i_{j,t,d} = \frac{\exp\left(X_{j,t,d}\beta - p_{j,t,d}\alpha_{\ell(i)} + \xi_{j,t,d}\right)}{1 + \sum_{k \in J(t,d)} \exp\left(X_{k,t,d}\beta - p_{k,t,d}\alpha_{\ell(i)} + \xi_{k,t,d}\right)}.$$

Since consumers are one of two types, we define $s^L_{j,t,d}$ be the conditional choice probability for a leisure consumer (and $s^B_{j,t,d}$ for a business consumer). Integrating over consumer types, we have

$$s_{j,t,d} = \gamma_t s^B_{j,t,d} + (1-\gamma_t) s^L_{j,t,d}.$$

5.2 Stochastic Arrivals

The market shares determine the probability of an arriving customer purchasing, but the sparsity of observed sales forces us to model shares as unobserved. That is, we cannot simply average observed sales and equate to market shares because zero market shares can be due to zero consumer arrivals or no arriving consumers wanting to purchase. Observed sales in the data are $q_{j,t,d}$, which are not only a function of the product shares, but also the number of people that arrive in each time period. This is important because in periods with low arrivals, the probability of $q_{j,t,d} = 0$ is quite high, but the probability of $s_{j,t,d} = 0$

is always zero. Thus, when we observe few arrivals, we must properly account for the sampling variation to be expected in sales quantities.

We assume consumer arrivals follow a Poisson distribution with rate $\lambda_{t,d}$. We adjust the model because we do not observe all searches—for example, a consumer who searches and purchases through a travel agency will result in a sale without associated search activity. To account for a fraction of observed searches, we use an exogenous, fixed-proportion scaling parameter ζ_t. By assuming preferences do not vary across booking channels, we can use a property of the Poisson distribution and simply scale up estimated Poisson rates using the fraction of observed bookings through the direct channel. It follows that

$$A_{t,d} \sim \text{Poisson}\Big(\lambda_{t,d} \cdot \zeta_t\Big).$$

Three assumptions allow us to construct analytic expressions for demand: (i) arrivals are independent of price (Section 3.3); (ii) consumers have no knowledge of remaining capacity; (iii) consumers solve the above utility maximization problems. With these assumptions, conditional on prices and product characteristics, demand for flight j is independent of the demand for flight j' and is distributed Poisson, i.e.,

$$\tilde{q}_{j,t,d} \sim \text{Poisson}\Big(\lambda_{t,d} \cdot s_{j,t,d}\Big).$$

With our random rationing assumption, demand may be censored, i.e.,

$$q_{j,t,d} = \min\Big\{\tilde{q}_{j,t,d}\,,\, C_{j,t,d}\Big\}.$$

6 Estimation

6.1 Using search information to separate arrivals from preferences

Observing arrival data allow us to address the common issue of missing "no purchase," or consumers who arrived and decided not to purchase. Although the estimation procedure

described below jointly estimates arrivals and preferences, identification of the model parameters come from distinct data series. The arrival process is estimated from consumer search data. This is similar to a Poisson regression model in that the arrival rates correspond to regression coefficients of search counts on a vector of control variables. With these estimates, we explicitly model the probability of observing various sales quantities.

Estimation is complicated for two reasons. First, the full model contains an unobservable component of demand that is potentially correlated with price. We assume a particular correlation structure between this demand shock and price. We address price endogeneity with instrumental variables. In our empirical application, we use cost shifters and variables that proxy for the opportunity cost of capacity. Second, the full model also has random coefficients that capture unobserved heterogeneity in consumer preferences. We estimate the price coefficient and the probability of each consumer type based on the distribution of sales, conditional on prices and the arrival rates. Our empirical approach matches the distribution of sales to predicted model sales, given the estimates of the arrival process.

6.2 Empirical Specification

Because consumer arrivals are observed at the t, d level, we cannot estimate the arrival process at the same granularity. Instead, we estimate the arrival process assuming a multiplicative relationship between day before departure and departure dates. Specifically, we assume that arrivals are parameterized as

$$\lambda_{t,d} = \exp(\lambda_t + \lambda_d).$$

This restriction assumes arrival growth towards departure (true in the data) evolves proportionally across departure dates. We pursue this parameterization because searches tend to increase over time (λ_t) but there are also strong departure date effects (λ_d). These parameters are also route-specific.

We assume consumer utility is given by

$$u_{i,j,t,d} = \beta_0 - \alpha_{\ell(i)} p_{j,t,d} + \text{FE(Time of Day } j) + \text{FE(Week)} + \text{FE(DoW)} + \xi_{j,t,d} + \varepsilon_{i,j,t,d},$$

where "FE" denotes fixed effects for the variable in parentheses. This flexibility in the utility and arrivals allows for rich substitution patterns, including seasonality effects, day-of-week effects, etc.

We parameterize the probability an arrival is of the business type as

$$\gamma_t = \frac{\exp\Big(f(t)\Big)}{1 + \exp\Big(f(t)\Big)},$$

where $f(t)$ is an orthogonal polynomial basis of degree five with respect to days from departure. This parametric assumption allows for a non-monotonic relationship between the composition of consumer types and time while producing values bounded between zero and one.

Finally, we allow for the relationship between the unobserved demand shock ξ and prices to change over the booking horizon. The correlation structure is allowed to vary across four equally sized blocks over the booking horizon. This captures varying managerial intervention in pricing over time that we observe in the data and that analyst manual management of price-setting may have little impact when arrivals are particularly low.

6.3 Estimation Procedure

We use a hybrid-Gibbs sampler to estimate route-specific parameters. Estimation is split into several distinct parts: arrivals, shares, demand parameters, and the price endogeneity parameters. With Poisson arrivals, we can rationalize zero sale observations while maintaining a Bayesian IV correlation structure between price and ξ. We use a Hybrid-Gibbs sampler algorithm that involves several Metropolis-Hastings steps to sample parameters. Shares are treated as unobserved, and we augment the data by sampling from their dis-

tribution. By conditioning on these shares, we are able to maintain an invertible demand system.[22]

We apply a data-augmentation approach to deal with unobserved shares, which complicates our estimation substantially. For every good in each market, there is an unobserved share that we must sample. In addition to shares, there are $T + D - 1$ arrival parameters, as well as fixed effects for time of departure, day of the week, and week of departure. We build upon the estimation procedure developed by Jiang, Manchanda, and Rossi (2009) and note that the data augmentation and search components in the Poisson demand model increase the estimation complexity tremendously. The sheer number of parameters in the model makes calibration of search distributions more difficult and as a result, we rely on a grid search to calibrate these distributions.

6.4 Identification and Instruments

The difficulty in estimating a model with aggregate demand uncertainty is addressing the problem of separably identifying shocks to arrivals from shocks to preferences. With data on the arrivals process, we directly observe variation in the market size and are able to condition on it to pin down the preference parameters. The variation that is used to identify the preference parameters is the same variation commonly cited in the literature on estimating demand for differentiated products using market level data (Berry, Levinsohn, and Pakes, 1995; Berry and Haile, 2014, 2016). The flight-level characteristic parameters are identified from the variation of flights offered across markets and the price coefficients are identified from exogenous variation introduced by instruments.

We use the carrier's shadow price of capacity (an output of the revenue management software), plane capacity, and total number of inbound or outbound bookings from a route's hub airport as our instruments.[23] The shadow price informs the opportunity cost of capacity.

[22]For a comprehensive look at our estimation procedure, please see Hortaçsu, Natan, Parsley, Schwieg, and Williams (2021).

[23]For a route with origin O and destination D, where D is a hub, the total number of outbound bookings from the route's hub airport is defined as the following; $\sum_{i=1}^{K} Q_{D,D'}$. Where $Q_{D,D'}$ is the the total number of bookings in period t, across all flights, for all K routes where the origin is the original route's destination.

The plane capacity captures the fact that the opportunity cost of selling one seat is lower for a larger plane serving the same route as well as capturing variation in price that comes from a last minute changes in equipment. The total number of inbound or outbound bookings to a route's hub airport captures the change in opportunity cost for flights that are driven by demand shocks in other markets. For example, for a flight from A to B, where B potentially provides service elsewhere and is a hub, we use all traffic from B onward to other destinations C or D. We assume demand shocks are independent across markets, so shocks to $B \rightarrow C$ and $B \rightarrow D$ are unrelated to demand for $A \rightarrow B$. Thus, a positive shock to onward traffic, out of hub B, will raise the opportunity cost of serving $A \rightarrow B \rightarrow C$ or $A \rightarrow B \rightarrow D$. This propagates to price set on the $A \rightarrow B$ leg.

7 Demand Estimates using Search and Sales Information

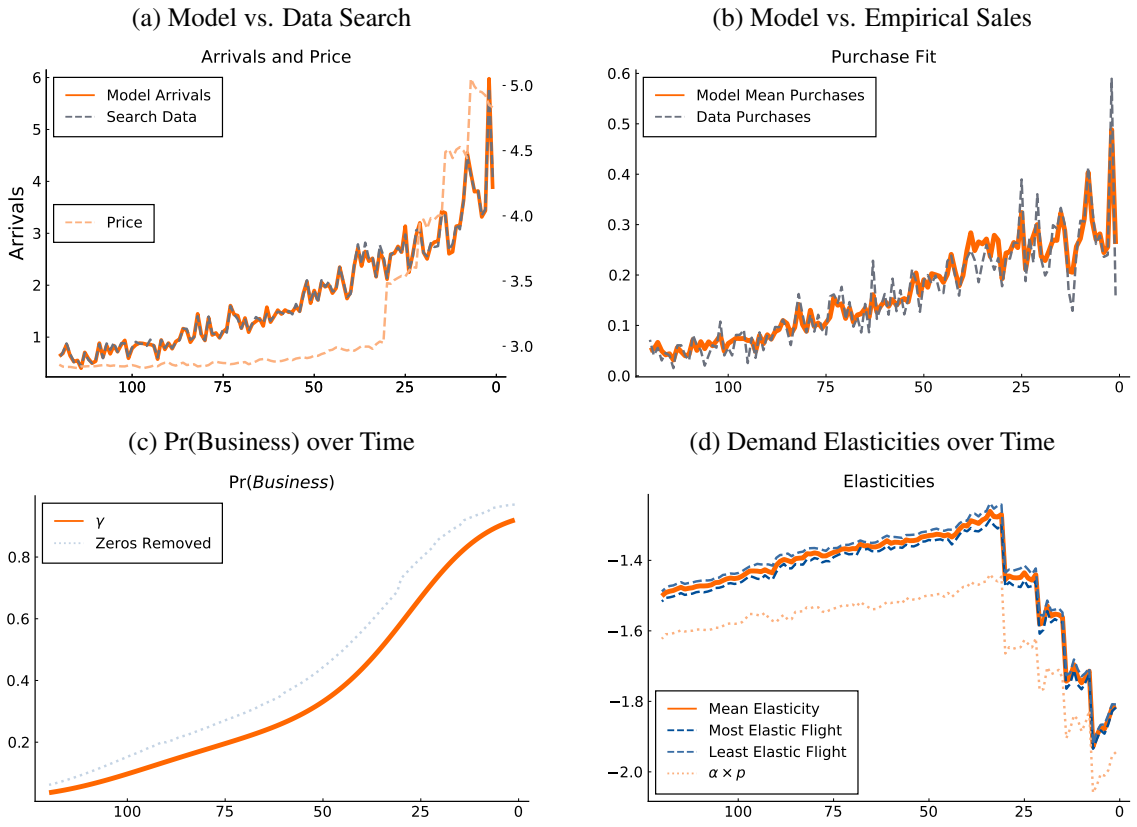
We estimate demand for 40 markets that best control for factors not modeled. We restrict our attention to routes where our air carrier is the only airline providing nonstop service. We show detailed demand results for a single market and then present demand summaries across markets.

Our example route demonstrates the challenges of estimating demand in this setting and the features of our data that allow us to recover preferences. For this route, 92% percent of observations have zero product sales. This is not an outlier route in our data. For this route, the airline offers a few nonstop flights a day, and seasonality is an important feature of demand. We report demand estimation results in Figure 7. Panel (a) shows how our estimates of Poisson arrivals fits the scaled up arrival data. The fit is very good because our specification includes d and t-specific parameters. Arrival rates are increasing toward the deadline. This is a common feature of the data. Panel (a) also shows average flight prices, increasing from $300 to over $500 in 120 days. Almost all routes we investigate contain

If the route's origin is the hub, we calculate the total number of inward bound bookings, which would be; $\sum_{i=1}^{K} Q_{O',O}$. Where $Q_{O',O}$ is the total bookings from all K routes where the original routes origin is the destination.

this feature.

Figure 7: Model Estimates for Route 1



Note: The horizontal axis of all plots denotes the negative time index, e.g. zero corresponds to the last day before departure. (a) Normalized model fit of searches with data searches. (b) Model fit of product shares with empirical shares. (c) Fitted values of γ_t over time, along with the probability a consumer is business conditional on purchase. (d) Mean product elasticities over time, along with the least and most elastic flights.

Panel (b) shows the average sales across booking horizon. Although there is significant noise in bookings over the horizon, our model smooths over some of this noise, following the patterns in arrivals. The differences between the data paths in panel (a) and (b) show the effects of having both shares and search in our model. Shares are decreasing as the departure date approaches, but only slightly, despite the large increase in price. This indicates that later arrivals are less sensitive to price changes, but still react to the increasing price. Despite shares falling, overall purchases still increase due to the magnitude of searches increasing toward the deadline.

Table 3: Demand Estimates Summary across Markets

Parameter	Mean	Std. Dev.	Median	25th Pctile.	75th Pctile.
Monday Arrivals	4.041	2.829	3.463	2.209	4.894
Tuesday Arrivals	3.323	2.479	2.812	1.679	3.905
Wednesday Arrivals	3.676	2.871	2.931	1.893	4.050
Thursday Arrivals	4.183	2.987	3.569	2.072	4.952
Friday Arrivals	4.453	2.984	3.874	2.304	5.565
Saturday Arrivals	2.898	1.914	2.484	1.487	3.734
Sunday Arrivals	4.284	2.874	3.860	2.347	4.865
Day of Week Spread	32.83	25.75	24.46	14.70	40.51
Flight Time Spread	82.83	68.60	64.77	31.66	103.12
Week Spread	66.68	74.00	39.34	28.31	71.58
Intercept	-1.706	1.447	-1.202	-2.314	-0.805
α_B	0.238	0.155	0.201	0.105	0.352
α_L	1.433	0.772	1.213	0.893	2.151

Note: Spread refers to the dollar amount a leisure consumer would pay to move from the least preferred time or day offered to the most preferred time or day of week.

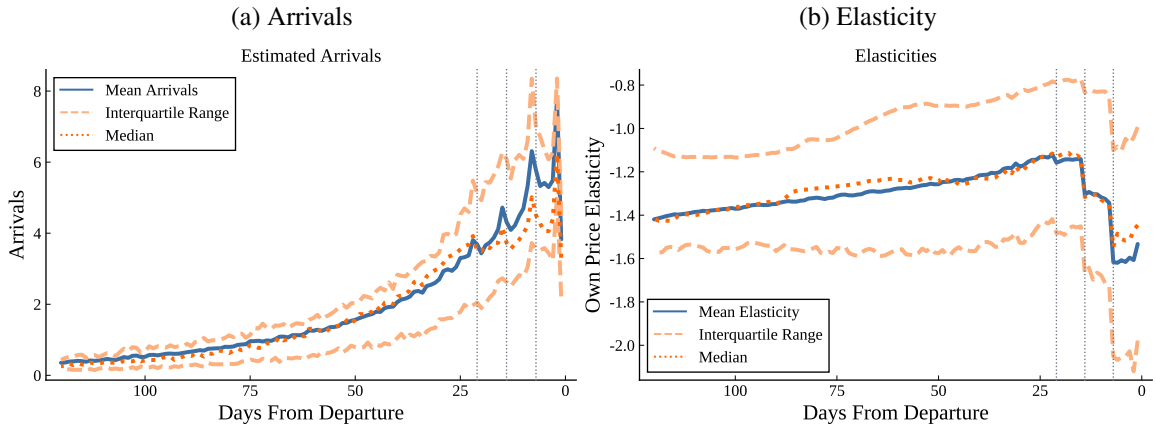
Panel (c) reports our estimates of the probability of business. There is a significant change in the composition of arriving consumers over the booking horizon, starting with a very low probability of business and ending close to one. The significant changes in the composition of arriving customers over time suggests elasticities become more inelastic. This is shown in panel (d). Elasticities start at -1.4 and increase through -1.2 before large price changes occur. Note that elasticities become more elastic close to departure, but this coincides with prices increasing by over 50%. This pattern is common among routes where the firm tends to sell most capacity. We identify this route as having moderately elastic demand with substantial day of the week heterogeneity in preferences.

We show several aggregated preferences across routes in Table 3. Dollar amounts represent a leisure consumer's willingness to pay. We find significantly heterogeneity across routes in both arrivals and consumer preferences. Time of departure preferences vary. Consumers generally prefer mornings and late afternoons. We estimate that some weeks have systematically higher demands than other weeks. In general, consumers who purchase

tickets close to departure are much less price sensitive than consumers who purchase well before the departure date. The heavy skew in preferences for flight time and week preferences highlight the heterogeneity in estimates across routes.

Figure 8-(a) plots arrivals for the mean route as well as the interquartile range over routes. The route with 75^{th} quantile of arrivals has more than double the amount of arrivals as the route at the 25^{th} quantile. This variation in market size highlights the importance of including route-specific parameters. In panel (b), we plot own-price elasticities. The plot confirms the pattern shown with our example market holds more broadly. On average, consumers become less price sensitive as the departure date approaches. The drop off in elasticites close to the departure date reflect the large price increases that occur after advance-purchase discounts expire.

Figure 8: Aggregate Arrivals and Elasticities



(a) Estimated Arrivals aggregated over all 40 routes. (b) Estimated Own Price Elasticity of demand aggregated over all 40 routes

Inspecting our demand estimates more closely, it is clear that routes tend to cluster in characteristic space. We identify three groups: routes to spoke or smaller cities, routes with heavy “business" traffic, and routes that largely serve leisure consumers. We discuss our demand estimates for each group.

Routes to small, or spoke cities, make up 75 percent of our estimated routes. These routes typically feature lower prices. The directionality of travel matters. We find con-

sumers tend to be less price sensitive leaving the larger airport (to the spoke), than the return. For several routes in this category, we estimate inelastic demand (demand elasticity > -1) close to the departure date as the percentage of business arrivals increases. On the other hand, we also identify a subset of routes in this category where price increases tend to be more driven by changes in remaining capacity. For these routes, we estimate fairly elastic demand, regardless of when tickets are sold.

We classify routes as being heavy in business traffic if we can identify large entities—either government, universities, or large corporate offices—that likely impact travel patterns to that city. We estimate that these routes tend to feature price inelastic demands close to departure. Our probability of business parameters are close to the one for late arrivals in these markets. These routes also typically feature more business arrivals earlier in the booking horizon. These routes make up 15 percent of the routes investigated.

We classify routes as leisure focused if there is a strong seasonality component to demand. These routes are marked by higher price sensitivity close to the departure date. Our example route falls into this category. There are 4 of these routes in our sample. These routes also feature strong preferences for time of day of departure. Because of the seasonal nature, there is significant heterogeneity in week of departure across routes as well. Some markets in this grouping feature quite elastic demands. These groups of leisure routes also feature different paths of price sensitivity than the others, breaking the otherwise established pattern of rapidly decreasing price sensitivity close to dept.

8 Demand Estimates using Forecasting Data

We have identified several pricing frictions that suggest the firm's forecast may differ from our empirical estimates. We have also established that demand is sometimes inelastic, especially close to the departure date, suggesting that prices are too low. Here, we ask, *What does the firm believe demand looks like?* To answer this question, we combine our demand results with micro forecasting data.

We proceed in two steps. First, we recover firm beliefs on the arrival processes. We assume the firm uses same model of consumer arrivals and that the total intensity of demand is the same as our estimates, i.e., $\lambda_{t,d} = \lambda_t \lambda_d$. However, we allow the composition of arriving customers to vary. To do this, we bring in output from an algorithm that assigns the reason for travel for every search and booking. "Leisure" and "business" make up an overwhelming majority of all classifications.[24] For every route, we calibrate γ_t as

$$\gamma_t^{\text{beliefs}} = \frac{\sum \text{Arrivals}_t^B}{\sum \text{Arrivals}_t^B + \sum \text{Arrivals}_t^B},$$

where Arrivals_t^B is the total number of arrivals classified as business for route r (L is similarly defined). With these estimates firm beliefs on the arrival process are $\lambda_t \lambda_d \gamma_t^{\text{beliefs}}$ for business passengers, and $\lambda_t \lambda_d (1 - \gamma_t^{\text{beliefs}})$ for leisure traffic. We label these Poisson distribution rates as $\tilde{\lambda}_{t,d}^B$ and $\tilde{\lambda}_{t,d}^L$, below. This approach is flexible in that it creates t-specific arrival rates may differ from our estimates; however, it is restrictive in the sense that it keeps the overall intensity of arrivals the same.

Second, we aim to recover firm beliefs on preferences, which may differ from our estimates. For this exercise, we use granular forecasting data (EQ) that report the expected sales at the level of flight (j), departure date (d), days from departure (t), forecasting period (s), passenger type (B/L), and price (p). The difference between s and t defines how far in advance the forecast is constructed. As an example, we observe the forecast for a flight three days before departure, forecasted 100 days before departure. Therefore, the forecast was constructed $(100-3)$ periods in advance. An observation such that $s = t$ implies the forecast is for the current period. Define Δ to be all combinations of differences between s and t, i.e.,

$$\Delta = \{(s-t) \,|\, \forall\, t \leq s \leq T \text{ and } 0 \leq t \leq T\} \in \mathbb{N}.$$

We assume the firm also uses a Poisson demand model, with the same specification as ours. Our descriptive analysis suggests that prices do not respond to substitute demand

[24] We ignore the other small categories for this exercise.

shocks, therefore, we consider a single product setting when recovering beliefs. We transform the forecasting data to a cumulative forecast that provides a direct analogue to our model,

$$\tilde{Q}^i_{j,k,t,d} := \sum_{k' \geq k} E Q^i_{j,k',t,d},$$

which is the forecast at fare buckets greater than or equal to k for consumer type i. In addition, we assume the forecasting model assigns $\tilde{\lambda}^B_{t,d}$ as the arrival process for all flights.[25] With this additional assumption, note that this cumulative forecast is equal to the model analogue $\tilde{\lambda}^B_{t,d} s^B_{j,k,t,d}(\cdot)$. That is, our assumptions imply that the unconstrained forecast is simply the Poisson demand rate for the given index.

We equate the forecasting data to its model analogue,

$$\tilde{Q}^i_{j,k,t,d} = \tilde{\lambda}^i_{t,d} s^i_{j,k,t,d}(\cdot).$$

If we take logs of the equation above and subtract the log of the outside good, we utilize the inversion of Berry (1994) to obtain the following estimation equation

$$\log\left(\frac{\tilde{Q}^i_{j,k,t,d}}{\tilde{\lambda}_{t,d}}\right) - \log(s^i_{0,t,d}) = \log(s^i_{j,k,t,d}) - \log(s^i_{0,t,d}) = \tilde{\delta}^i_{j,k,t,d}. \tag{1}$$

The reason why we can immediately obtain an estimating equation with the forecasting data is that it is at the consumer-type level, thus avoiding the need to use the contraction mapping in Berry, Levinsohn, and Pakes (1995) and Berry, Carnall, and Spiller (2006). The inversion allows us to impose similar restrictions imposed in our model, i.e., the only difference in mean utility across consumer types is on the price coefficient.[26]

Defining the left-hand side of Equation 1 above as $\tilde{\delta}$, we obtain a linear estimating

[25] Instead, we could assume arrivals are $\tilde{\lambda}^i_{t,d}/J$, so that each flight receives $1/J$ of arrivals. This increases product shares and results in consumers estimated to be more price insensitive.

[26] We must also confront a data limitation in that our forecasting data is not necessarily at the t level, but rather, at a grouping of ts the firm uses for decision making. The number of days in a grouping varies. We address this data feature in the following way. Note that our demand model does not have t-specific parameters—preferences do not vary by day before departure. Therefore, if $\tilde{Q}^i$ is the forecast for consumer

equation of the form

$$\tilde{\delta} = X\tilde{\beta} - \tilde{\alpha}p + \xi + u,$$

where $\tilde{\beta}, \tilde{\alpha}^B, \tilde{\alpha}^L$ are recovered firm beliefs about demand[27,28]

In Figure 9, we provide a visual summary comparing the model predictions using our demand estimates (Model E) from those recovered from the forecasting data (Model B). In panel (a), we plot product shares for both passenger types over time. Product shares are similar for business customers, with Model B shares being slightly higher. The drop in shares close to departure occurs because fares increase substantially. There is a significant spread in the probability of purchase for leisure consumers, with Model B shares being significantly higher. Therefore, Model B results in consumer types being "closer together" than under Model E. In panel (b), we plot the probability that an arriving customer is a business traveler. Model E places more mass on business travelers and produces larger changes in the types of consumers arriving over the booking horizon. Model B produces a

type i for multiple periods, the model analogue to this is

$$\tilde{Q}^i_{\cdot,t^*} = \sum_{t \in t^*} \tilde{\lambda}^i_{\cdot,t} s^i_{\cdot,t}(\cdot) = \left(\sum_{t \in t^*} \tilde{\lambda}^i_{\cdot,t} \right) s^i_{\cdot}(\cdot).$$

We can simply sum over the relevant time indices for arrival rates because the time-index does not enter within-consumer type shares, and the forecasting data assumes a constant price within a grouping of time. This is important because we can then define consumer-type product shares as

$$\frac{\tilde{Q}^i_{\cdot,t^*}}{\sum_{t \in t^*} \tilde{\lambda}^i_{\cdot,t}} = s^i(\cdot).$$

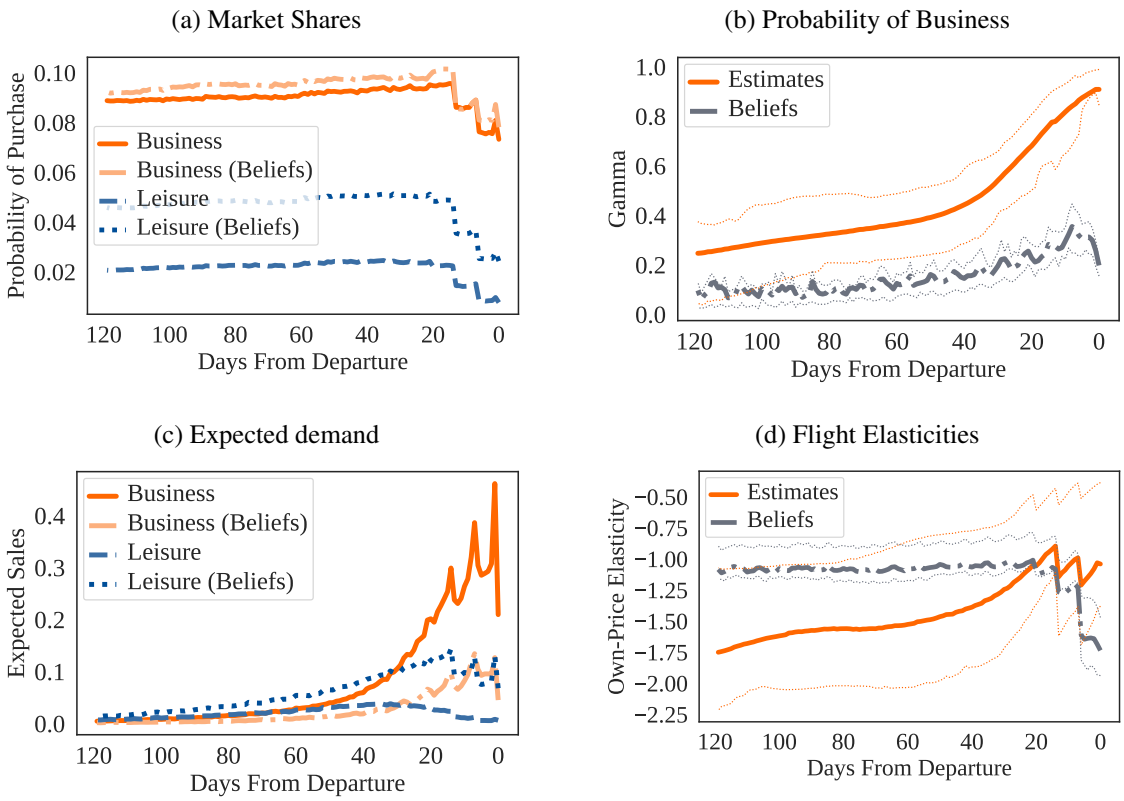
Thus, we obtain the following inversion,

$$\log\left(\frac{\tilde{Q}^i_{\cdot,t^*}}{\sum_{t \in t^*} \tilde{\lambda}^i_{\cdot,t}} \right) - \log(s^i_0) = \log(s^i) - \log(s^i_0) = \tilde{\delta}^i. \tag{2}$$

[27] We also include ξ in the model. We use the mean of the posterior for that observation taken from our estimates. Thus, this approach also identifies a firm "ξ" that also differs across consumer types. We set these residuals equal to zero after recovering firm beliefs.

[28] We also estimate two additional specifications by including Δ and $\tilde{\beta}^\Delta, \tilde{\alpha}^\Delta$-specific parameters. Adjustments in the parameters over $(s-t)$ inform how the firm updates its forecasts. Finally, we consider $\tilde{\beta}^{\Delta \times T}, \tilde{\alpha}^{\Delta \times T}$, so that firm beliefs depend not only on $(s-t)$, but also on t. We do not find evidence of learning about consumer preferences, as deviations between between the belief estimates and model estimates do not converge across Δ or $\Delta \times T$.

Figure 9: Firm Beliefs on Demand



Note: (a) Comparison of product shares across consumer types, over time. (b) Estimates of γ_t versus those calculated using the passenger assignment algorithm. (c) Forecasted demand across consumer types, over time. (d) Comparison of own-price elasticities over time. (b) and (d) contain the 25th and 75th percentiles. Results are reported averaging over all observations in the data.

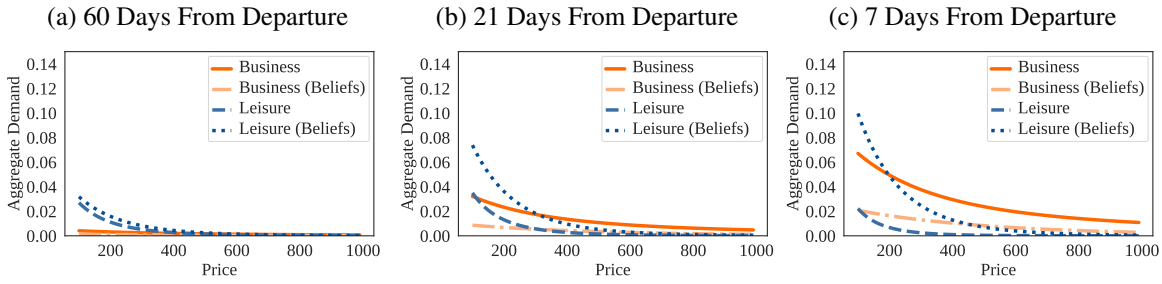
small drop in business consumer arrivals very close to departure.

Panel (c) depicts expected demand. Although we identified preferences being similar for business customers (panel a), the significant differences in γ_t creates a sizeable gap in business passenger demand close to departure. Model E results in more purchases close to departure. Model B results in leisure purchases close to departure, whereas Model E suggests very few leisure travelers buy close to the deadline. Finally, in panel (d), we plot own-price elasticities over time. Model E produces elasticities that are increasing (toward zero), whereas Model B results in mostly constant elasticities that then drop close to departure. Overall, Model B yields slightly more inelastic demand well in advance of the departure date; however, aggregate demand is low here. The models diverge as the

departure date approaches.

In order to better understand what the two models imply concerning consumer behavior, in Figure 10 we plot demand for three separate time periods (60, 21, and 7 days before departure, respectively). Each panel contains four demand curves, one for each model and consumer type combination. Well before departure, both models yield quantitatively similar demand curves because arrivals are low. At 21 days before departure, the demand curve under Model B for leisure travelers is higher, but more elastic, than Model E. The level of business demand is also noticeably higher under Model B. Panel (c) shows significant differences across consumer types and models. Business demand is much higher under Model E, and Leisure demand is significantly higher under Model B, particularly at lower prices.

Figure 10: Aggregate Demand



Notes: (a)-(c) The demand curve for continuous prices between \$100 and \$1,000. The unobservable (ξ) is held fixed over prices. Results are reported averaging over flights for a given route and then across routes.

Overall, the two models are quite different. Model B yields more compressed demand elasticities where aggregate demand is slightly more inelastic than compared to Model E. This is driven by the upward bias in the forecasting data along with reduced variance in the forecasts across flights (relative to bookings). Model E suggests there is more heterogeneity in demand across both flights and routes, with a more pronounced change in arriving consumer preferences over time. Very close to departure, Model E produces more inelastic demand than under Model B, aggregate demand differs due to differences in γ_t over time. In Section 9, we use counterfactuals in order to quantify the impacts of the forecasting data

yielding different demand elasticities than those estimated using the sales and search data.

9 Counterfactual Analysis of Pricing Frictions

We estimate the welfare impacts of addressing the organizational frictions that we have identified. We outline the counterfactual models in Section 9.1. We discuss implementation in Section 9.2. Our results can be found in Section 9.3.

9.1 Counterfactual Models

We consider several scenarios. Our baseline model tries to approximate present pricing practices. We use the demand estimates calibrated from the biased forecasts managed by the RM department (Model B). Additionally, we use the observed fares filed by the pricing department. We select the EMSR-b heuristic to determine inventory allocation as it well approximates what the firm actually does.

Next, we correct a single pricing bias and leave others uncorrected. We substitute the Model B demand estimates for the Model E demand estimates. This corrects for persistently biased forecasts. We leave the set of fares used in the heuristic fixed.

In the third counterfactual, we use the biased forecasts (Model B) but alter the fares inputted to the algorithm. We select these fares by noting that EMSR-b itself is biased (Wollmer, 1992). EMSR-b works by limiting the number of seats that can be sold at a particular fare class—lower fare classes are only blocked in order to save capacity for future sales at a higher price. EMSR-b does not address fares that are set below the revenue maximizing price. There are cases where capacity is not binding and prices will drop well below the revenue maximizing price. With “coordinated fares," we input fares for each day before departure that enforces pricing on the elastic side of the demand curve. We consider the case in which capacity is infinite. In this scenario, there is no incentive to hold capacity for future periods implying capacity costs are zero, and prices solve $MR = 0$. We use this as the lowest fare. Then, we increase fares by scaling this fare by a constant from 1.0×

to 2.5× for 13 total fare classes. We do not remove the availability of any fares in this counterfactual as fares are specific to each pricing period.

Finally, we address frictions introduced by both the RM and pricing departments. We use the unbiased forecasts (Model E) along with fares coordinated with Model E demands using the procedure just outlined.

Note that by using EMSR-b as the firm's pricing rule, other biases remain that have not been addressed. First, EMSR-b is a heuristic and not necessarily optimal. In addition, EMSR-b is a single-product revenue solution, so it does not allow for the pricing of substitutes. We can address these biases by solving a dynamic pricing problem. We follow the dynamic pricing (DP) problem in Williams (2021) where a firm selects a price for each flight from a discrete set of prices that maximizes its current and expected future profits. We assume that the firm solves the following problem,

$$V_t(C_t, p_t) = \max_{p \in P_t} \left(\mathrm{R}_t^e(C_t, p_t) + \mathrm{EV}_{t+1}(C_{t+1}, p_{t+1} \,|\, C_t, p_t) \right),$$

where C_t is the vector of remaining capacity for each flight offered in that time period, p_t is the vector of prices the firm selects, and $R_t^e(C_t, p_t)$ is the firm's expected flow revenue. These value functions are specific to a route and departure date (we suppress this notation above).

We consider two versions of the DP. We first simulate pricing for each flight independently, assuming other flights will be missed at the lowest priced fare. This is analogous to how we proceed with EMSR-b. We then consider a multi-product DP in which substitutes are endogenously priced. We limit ourselves to $|J| = 2$ due to the dimensionality of the more complicated environments.

Using Model E estimates suggests that the firm knows the arrival (and demand) processes at the beginning of time. This may be unreasonable given that we have provided evidence that the firm re-forecasts flights at regular intervals.[29] To keep our counterfactual

[29] As discussed in Section 4.3, we do not find evidence that the firm updates correctly (toward our estimates) over time.

simulations manageable, we investigate pricing in which the firm does not update beliefs at all, but rather, assumes all departure dates are identical. Specifically, we consider a scenario in which the firm uses the average arrival rate—over both departure dates and day before departure—when pricing. We similarly average over all preferences (except the probability of business and price sensitivity), and use those for pricing. This "average world" represents a point of comparison where the firm is aware of how to target customers over time, but is not aware of the levels of demand or arrivals for any particular flight.

9.2 Counterfactual Implementation

For each counterfactual, we simulate flights based on the empirical distribution of observed remaining capacity 120 days before departure. For each vector of initial remaining capacities, we then draw preferences and arrival rates given our demand estimates (Model E). We simulate 10,000 flights for each initial capacity, demand combination. Like our demand model, we do not endogenize connecting (or flow) bookings[30] Therefore, we handle connecting bookings through exogenous decreases in remaining capacity, based on Poisson rates estimated using changes in observed remaining capacity not due to nonstop bookings (which could be award tickets, connecting bookings, etc.).[31] Consumers are assumed to arrive in a random order within a period. If demand exceeds remaining capacity, consumers are offered seats in the order they arrive. That is, if the lowest-priced fare has a single seat and is sold immediately, the next arriving consumer within a period is offered the next least-expensive fare.[32]

[30] We do not observe all the data requirements to estimate such a model.

[31] Alternatively, we could subtract off observed connecting bookings from the initial capacity condition. However, this constrains initial capacity and results in higher prices than what we observe in the data.

[32] Contrary to our demand model, consumers may face different prices in the same market in our simulation. This occurs rarely in our simulations.

9.3 Welfare Comparison and Addressing Organizational Frictions

We report our main counterfactual results in Table 4. Our baseline model—used to approximate present day pricing practices—is shown in the first row. We normalize baseline too 100% for all welfare measures (consumer surplus leisure and business, revenues, and welfare). Rows two through four present counterfactuals in which a single or multiple pricing biases are corrected. Results are reported in percentage differences.

Table 4: Counterfactual Estimates and a Comparison to Present Practices

	Counterfactual	CS_L	CS_B	Rev	W
1)	Observed Fares and Biased Forecasts	100.0	100.0	100.0	100.0
2)	Coordinated Fares Given Biased Forecast	97.6	100.1	101.4	100.0
3)	Unbiased Forecasts Given Observed Fares	99.7	99.8	100.2	100.0
4)	Coordinated Fares and Unbiased Forecasts	58.2	69.9	123.4	86.7

Note: In counterfactual (1), we approximate current pricing practices. Counterfactual (2) and (3) address a single organizational team bias, but leave others in place. Finally, in counterfactual (4), we consider a scenario in which RM and pricing department decisions are coordinated.

We find that if a single organizational team corrected one pricing bias and other teams' biases remained in place, outcomes are very similar. As the table shows, in rows one through three, all numbers are close to 100%. Consider coordinating fares to the incorrect forecast. In this case, Model B demands are considerably more elastic close to the departure date as compared to Model E. If prices are tailored to the biased forecast, overall price levels are too low. The firm does not internalize that late-arriving consumers are quite price insensitive, this lowers opportunity costs throughout the booking horizon, and results in coordinated prices being too low. Alternatively, consider the case where the forecast is corrected but current fares are used as an input. Now, the opportunity costs of capacity rise, as the firm internalizes the benefit of saving seats toward the deadline. However, conditional saving these seats, the price inputs are too low to extract surplus from business customers. Therefore, outcomes are nearly unchanged.

When the unbiased forecast is used along with coordinated prices to that unbiased forecast, outcomes are very different. This is shown in row (4). Relative to the other counterfactuals, prices are much higher, revenues are higher, consumer surplus is lower, and dead-weight loss increases. By coordinating inputs, the effectiveness of the algorithm at extracting consumer surplus is much higher. This is because of the complementarity of saving seats for business customers (achieved with EMSR-b and the corrected forecast) and then charging high prices (achieved with a coordinated pricing menu to the forecast).

Table 5: Counterfactual Estimates under an Alternative Pricing System

	Counterfactual	CS_L	CS_B	Rev	W
4)	Pricing heuristic EMSR-b	100.02	100.0	100.0	100.0
5)	Single-J Dynamic Pricing	94.1	99.0	100.7	99.6
6)	Multi-J Dynamic Pricing	77.4	94.0	100.0	96.0

Note: In counterfactual (4) prices are set using EMSR-b with Model E and the coordinated price menus. Counterfactual (5), endogenously sets prices for each flight independently using the DP. Finally, counterfactual (6) we jointly set prices of all products in the same market using the DP.

We compare our core findings to the model of "persistently average beliefs," or where the firm prices according to avg(λ) and avg(β). We find that even with average beliefs, results are fairly similar to those estimated under corrected forecasts with tailored prices. Essentially, we find that knowing the average change in willingness to pay over time is very important, much more so than day of the week variation in preferences and peak versus off-peak flights. Even without the firm learning about demand, and having incorrect beliefs about arrivals, the firm can price to obtain outcomes near the full-information case. Correct beliefs about the price sensitivity over the booking horizon are the most important factor in optimizing price.

In Table 5, we compare EMSR-b with coordinated fares and the unbiased forecast to models of dynamic pricing that also use these inputs. The table includes routes in which two flights are offered a day. We report two rows after our EMSR-b results corresponding to the situation where the firm optimizes flight prices individually and one in which the

firm prices flights jointly. The reason we focus on two flights a day is due to computational complexity. Note that we use a common pricing grid for all counterfactuals. Outcomes under EMSR-b are normalized to 100%.

We find that outcomes are largely unchanged when moving from EMSR-b to DP. Since we only allow a single price in each time period per flight, the model has less flexibility when pricing to leisure consumers, often leading to a decrease in consumer surplus despite fares being similar. The added value of the dynamic program—properly maximizing for revenue and accounting for substitution—is minimal, as prices are chosen from a coarse pricing grid. For a finer pricing grid, such as what approximates continuous pricing, we would observe changes to allocative efficiency. When using a coarse pricing grid, the optimization tool used to choose optimal prices is not as important as the combination of correct forecast and prices consistent with that forecast.

10 Conclusion

In this paper, we document several ways in which sophisticated pricing systems do not respond to some key market features. These pricing frictions arise due to different organizational teams being responsible for separate inputs into the pricing system. We find that not coordinating on algorithm inputs curtails the ability of a large U.S. airline from optimizing price. This has important implications for welfare due to the complications of allocating seats in a dynamically evolving market environment.

We show that with present biases, the pricing algorithm is effective at filling seats, but could extract more revenue. If pricing frictions are addressed individually, outcomes are unchanged. This is because other biases are sufficiently strong that the pricing algorithm does not react to a single optimized input. We also show that if all pricing frictions are addressed simultaneously, this helps the firm optimize prices, but may increase dead-weight loss.

Beyond airlines, our results highlight the difficulty firms may have in designing organi-

zational structures around data and algorithms. When algorithms are complex and require numerous inputs, it may be infeasible for a single organizational team to monitor and manage all inputs. When firms delegate tasks to teams, and teams have distinct boundaries, this may prohibit potential complementarities in data-driven decision making.

References

Aguirregabiria, V., and J. Jeon (2020): "Firms beliefs and learning: Models, identification, and empirical evidence," *Review of Industrial Organization*, 56(2), 203–235.

Akepanidtaworn, K., R. Di Mascio, A. Imas, and L. Schmidt (2019): "Selling fast and buying slow: Heuristics and trading performance of institutional investors," Working Paper.

Alonso, R., W. Dessein, and N. Matouschek (2008): "When does coordination require centralization?," *American Economic Review*, 98(1), 145–79.

——— (2015): "Organizing to adapt and compete," *American Economic Journal: Microeconomics*, 7(2), 158–87.

Aryal, G., C. Murry, and J. W. Williams (2018): "Price Discrimination in International Airline Markets," Working Paper.

Athey, S., and S. Stern (2002): "The Impact of Information Technology on Emergency Health Care Outcomes," *RAND Journal of Economics*, pp. 399–432.

Belobaba, P. (1987): "Air Travel Demand and Airline Seat Inventory Management," Ph.D. thesis, Massachusetts Institute of Technology.

Belobaba, P. P. (1989): "OR practice-application of a probabilistic decision model to airline seat inventory control," *Operations Research*, 37(2), 183–197.

——— (1992): "Optimal vs. heuristic methods for nested seat allocation," in *Presentation at ORSA/TIMS Joint National Meeting*.

Berry, S., M. Carnall, and P. Spiller (2006): "Airline hubs: costs, markups and the implications of customer heterogeneity," *Advances in airline economics*, 1, 183–214.

Berry, S., and P. Haile (2014): "Identification in Differentiated Products Markets Using Market Level Data," *Econometrica*, 82(5), 1749–1798.

——— (2016): "Identification in Differentiated Products Markets," *Annual Review of Economics*, 8, 27–52.

Berry, S. T. (1994): "Estimating Discrete-Choice Models of Product Differentiation," *The RAND Journal of Economics*, pp. 242–262.

Berry, S. T., J. Levinsohn, and A. Pakes (1995): "Automobile Prices in Market Equilibrium," *Econometrica*, pp. 841–890.

Bloom, N., R. Sadun, and J. Van Reenen (2012): "The organization of firms across countries," *The quarterly journal of economics*, 127(4), 1663–1705.

Bresnahan, T. F., E. Brynjolfsson, and L. M. Hitt (2002): "Information technology, workplace organization, and the demand for skilled labor: Firm-level evidence," *The quarterly journal of economics*, 117(1), 339–376.

Brumelle, S. L., J. I. McGill, T. H. Oum, K. Sawaki, and M. Tretheway (1990): "Allocation of airline seats between stochastically dependent demands," *Transportation Science*, 24(3), 183–192.

Brynjolfsson, E., and P. Milgrom (2012): "1. Complementarity in Organizations," in *The handbook of organizational economics*, pp. 11–55. Princeton University Press.

Castillo, J. C. (2019): "Who Benefits from Surge Pricing?," *Available at SSRN 3245533*.

Che, Y.-K., and S.-W. Yoo (2001): "Optimal incentives for teams," *American Economic Review*, 91(3), 525–541.

Cho, S., G. Lee, J. Rust, and M. Yu (2018): "Optimal Dynamic Hotel Pricing," Working Paper.

Cho, S., and J. Rust (2010): "The flat rental puzzle," *The Review of Economic Studies*, 77(2), 560–594.

DellaVigna, S. (2018): "Structural behavioral economics," in *Handbook of Behavioral Economics: Applications and Foundations 1*, vol. 1, pp. 613–723. Elsevier.

DellaVigna, S., and M. Gentzkow (2019): "Uniform pricing in us retail chains," *The Quarterly Journal of Economics*, 134(4), 2011–2084.

D'Haultfœuille, X., P. Février, A. Wang, and L. Wilner (2019): "Estimating the Gains (and Losses) of Revenue Management," Working Paper.

Dubé, J.-P., and S. Misra (2021): "Personalized Pricing and Consumer Welfare," Working Paper.

Ellison, S. F., C. Snyder, and H. Zhang (2018): "Costs of managerial attention and activity as a source of sticky prices: Structural estimates from an online market," Discussion paper, National Bureau of Economic Research, Working Paper.

Gallego, G., and G. Van Ryzin (1994): "Optimal Dynamic Pricing of Inventories with Stochastic Demand Over Finite Horizons," *Management science*, 40(8), 999–1020.

Goldfarb, A., and M. Xiao (2011): "Who thinks about the competition? Managerial ability and strategic entry in US local telephone markets," *American Economic Review*, 101(7), 3130–61.

——— (2016): "Transitory shocks, limited attention, and a firms decision to exit," Discussion paper, Working paper.

Hendel, I., and A. Nevo (2013): "Intertemporal price discrimination in storable goods markets," *American Economic Review*, 103(7), 2722–51.

Hitsch, G. J., A. Hortaçsu, and X. Lin (2019): "Prices and Promotions in US Retail Markets: Evidence from Big Data," Working Paper.

Hortaçsu, A., O. Natan, H. Parsley, T. Schwieg, and K. Williams (2021): "Incorporating Search and Sales Information in Demand Estimation," Working Paper.

Huang, Y. (2021): "Seller-Pricing Frictions and Platform Remedies: The Case of Airbnb," Working Paper.

Ichniowski, C., K. Shaw, and G. Prennushi (1997): "The effects of human resource practices on manufacturing performance: A study of steel finishing lines," *American Economic Review*, 87(3), 291–313.

Jiang, R., P. Manchanda, and P. E. Rossi (2009): "Bayesian Analysis of Random Coefficient Logit Models using Aggregate Data," *Journal of Econometrics*, 149(2), 136–148.

Lazarev, J. (2013): "The Welfare Effects of Intertemporal Price Discrimination: an Empirical Analysis of Airline Pricing in US Monopoly Markets," Working Paper.

Littlewood, K. (1972): "Forecasting and control of passenger bookings," *Airline Group International Federation of Operational Research Societies Proceedings, 1972*, 12, 95–117.

Ma, Y., T. Ropele, D. Sraer, and D. Thesmar (2020): "A quantitative analysis of distortions in managerial forecasts," Working Paper.

Massey, C., and R. H. Thaler (2006): "The losers curse: Overconfidence vs. market efficiency in the National Football League draft," Working Paper.

McGill, J. I., and G. J. Van Ryzin (1999): "Revenue management: Research overview and prospects," *Transportation science*, 33(2), 233–256.

Siemsen, E., S. Balasubramanian, and A. V. Roth (2007): "Incentives that induce task-related effort, helping, and knowledge sharing in workgroups," *Management science*, 53(10), 1533–1550.

Sweeting, A. (2012): "Dynamic Pricing Behavior in Perishable Goods Markets: Evidence from Secondary Markets for Major League Baseball Tickets," *Journal of Political Economy*, 120(6), 1133 – 1172.

Talluri, K., and G. Van Ryzin (2005): *The theory and practice of revenue management*, vol. 68. Springer.

——— (2006): *The Theory and Practice of Revenue Management*, vol. 68. Springer Science & Business Media.

Williams, K. R. (2021): "Dynamic Airline Pricing and Seat Availability," Working Paper.

Wollmer, R. D. (1992): "An airline seat management model for a single leg route when lower fare classes book first," *Operations research*, 40(1), 26–37.

Online Appendix

A Pricing Heuristic - EMSR-B

We approximate the solution to a dynamic pricing (DP) problem using a well-known heuristic in operations research, Expected Marginal Seat Revenue-B or EMSR-B (Belobaba, 1987). The heuristic was developed in order to avoid solving highly complex dynamic pricing problems. The heuristic simplifies the firm's decision in each period by aggregating all future sales before the deadline into a single future period. It also simplifies the demand system to be for only a single product, so competitive effects cannot be considered. We describe this process below and show how to incorporate Poisson demand in EMSR-B. It is important to note that EMSR-B provides an allocation over a given finite set of prices, instead of providing the optimal price itself given any state of the world. If prices are updated continuously in a DP, expected revenues are clearly higher than EMSR-B due to integrating over all future demands when deciding the allocation for today. EMSR-B associates each price with a fare-class then chooses a maximal number of sales that can be made to each fare-class. This means that consumers may face different prices within a single pricing period when one class is closed and a higher priced class opens.

A.1 Littlewood's Rule

EMSR-B is a generalization of Littlewood's rule, which is a simple case where a firm prices two time periods uses two fare classes. A firm with a fixed capacity of goods (seats) wants to maximize revenue across two periods, where leisure (more elastic) consumers arrive in the first period and business (less elastic) consumers arrive in the second period. The firm sets a cap on the number of seats b it is willing to sell in the first period to leisure passengers. This rule returns a maximum number of seats for leisure when the price to both leisure and business customers has already been decided; it does not determine optimal pricing.

The solution equates the price of a seat sold in the first period (to leisure travelers) to the opportunity cost of lowering capacity for sales in the second period (business travelers). Given prices p_L, p_B, capacity C, and the arrival CDF of business travelers F_B, Littlewood's rule equates the fare ratio to the probability that business class sells out. The fare ratio is the marginal cost of selling the seat to leisure (the lower revenue p_L) which is set equal to the marginal benefit—the probability that the seat would not have sold if left for business customers only. Littlewood's rule is given by

$$1 - F_B(C - b) = \frac{p_L}{p_B}.$$

This equation can then be solved for b, the maximum number of seats to sell to leisure customers in period one. This solution is exact if consumers arrive in two separate groups and there are only two time periods and two consumer types.

A.2 EMSR-b Algorithm

The EMSR-B algorithm (Belobaba, 1987) extends Littlewood's rule to multiple fare levels or classes. For each fare class, all fare classes with higher fares are aggregated into a single fare-class called the "super-bucket." Once this bucket is formed, Littlewood's rule applies, and can be done for each fare class iteratively. Rather than just comparing leisure and business classes, the algorithm now weights the choice of selling a lower fare-class ticket against an average of all higher fare classes.

We apply the algorithm for K sorted fare-classes such that $p_1 > p_2 > ... > p_K$. Each fare class has independent demand with a distribution F_k. Under our specification, the demand for each fare class is distributed Poisson with mean μ_k that is given by future arrivals times the share of the market exclusive to that bucket.

The super-bucket is a single-bucket placeholder for a weighted average of all higher fare-class buckets. Independent Poisson demand simplifies this calculation, as the sum of independent Poisson distributions is itself Poisson. The mean of the super-bucket is the sum

of the mean of each higher fare-class bucket. The price of the super-bucket is a weighted average of the price of each higher-fare class, using the means as the weight.

For each fare class, Littlewood's Rule is then applied with the fare-class taking the place of leisure travel, and the super-bucket in place of business travel. It is assumed that all future arrivals appear in a single day. The algorithm then describes a set of fare-class limits b_k that define the maximum number of sales for each class before closing that fare class. We denote the remaining capacity of the plane at any time by C. The algorithm uses the following pseudo-code:

for $t > 2$ **do**

  for $k \leftarrow K$ **to** 1 **by** -1 **do**

    i) Compute un-allocated capacity $C_{k,t} = C - \sum_{i=k}^{K} b_i$,

    ii) Construct the super-bucket

$$\mu_{sb} = \sum_{i=1}^{k-1} \mu_i, \qquad p_{sb} = \frac{1}{\mu_{sb}} \sum_{i=1}^{k-1} p_i \mu_i, \quad F_{sb} \sim \text{Poisson}(\mu_{sb}),$$

    iii) Apply Littlewood's Rule using the super-bucket distribution as the demand for business

$$C_{k,t} - b_k = \min \left\{ {F_{sb}}^{-1} \left(1 - \frac{p_k}{p_{sb}} \right), C_{k,t} \right\}.$$

  end

end

In the case where $t = 1$, dynamics are no longer important, so there is no longer a need to trade off based on the opportunity cost. As a result, we limit the fare of the highest revenue class to all remaining capacity, and set limits of all other classes to zero.

A.2.1 Fare Class Demand

What remains is computing the mean μ_k for each fare class bucket. We detail the process in this section. Demand in each market is an independent Poisson with arrival rate $\exp(\lambda_t^t +$

$\lambda_d^d)s_j(p)$. Note that this p is a vector of the prices of all flights in the market. We assume that the firm believes other flights will be priced at their historic average over the departure date and day before departure. This allows us to construct a residual demand function $s_j(p_j)$ that is a function of the price of the current flight only. We will treat this as the demand for the flight at a given bucket's price for the remainder of this section.

Each fare class has a set price p_k, at any time t, departure date d we will see $\exp(\lambda_t^t + \lambda_d^d)$ arrivals, of which $s(p_k)$ are willing to purchase a fare for bucket k. However, $s(p_{k-1})$ are willing to purchase a fare for bucket $k-1$ as well, since they will buy at the higher price p_{k-1}. Only $\exp(\lambda_t^t+\lambda_d^d)\big[s_t(p_k)-s_t(p_{k-1})\big]$ are added by the existence of this fare class with price $p_k < p_{k-1}$. Note that this is a flow quantity—the amount of purchases in time t, but EMSR-B requires stock quantities: How many will purchase over the remaining lifetime of the sale?

What is the distribution of future purchases then? For the sake of the algorithm, we assume that once a fare class is closed, there are no purchases on the higher fare class until the next time period. Each day t is an independent Poisson process split by the share function. Independent split Poisson processes are still Poisson, so we may compute the mean of purchases solely in a fare class by summing arrivals over future time t, and taking the difference in shares between price p_k and p_{k-1}. For time t and departure date d, the stock demand for fare-class k is given by

$$\sum_{i=1}^{t} \exp(\lambda_i^t + \lambda_d^d)\big[s_t(p_k)-s_t(p_{k-1})\big],$$

where $s_t(p_0)=0$ for notational parsimony.

This demand distribution is only used to compute the super-bucket demand distribution. Note that we only include future stock demand in the super bucket, and thus only sum

arrivals until time $t-1$. For fare-class k. The super bucket's stock demand is given by

$$\mu = \left(\sum_{i=1}^{t-1} \exp(\lambda_i^t + \lambda_d^d) s_i(p_{k-1}) \right)$$
$$p = \frac{1}{\mu} \sum_{j=1}^{k-1} p_j \sum_{i=1}^{t-1} \exp(\lambda_i^t + \lambda_d^d) \left[s(p_j) - s(p_{j-1}) \right].$$

The updated pseudo-code for the EMSR-B algorithm is:

for $t > 2$ **do**

for $k \leftarrow K$ **to** 1 **by** -1 **do**

i) Compute un-allocated capacity $C_{k,t} = C - \sum_{i=k}^{K} b_i(t)$,

ii) Construct the super-bucket

$$\mu_{sb} = \left(\sum_{i=1}^{t-1} \exp(\lambda_i^t + \lambda_d^d) \right) s_i(p_{k-1}),$$
$$p_{sb} = \frac{1}{\mu_{sb}} \sum_{j=1}^{k-1} p_j \sum_{i=1}^{t-1} \exp(\lambda_i^t + \lambda_d^d) \left[s(p_j) - s(p_{j-1}) \right],$$
$$f_{sb} \sim \text{Poisson}(\mu_{sb}),$$

iii) Apply Littlewood's Rule using the super-bucket distribution as the demand for business.

$$C_{k,t} - b_k(t) = \min \left\{ {F_{sb}}^{-1} \left(1 - \frac{p_k}{p_{sb}} \right), C_{k,t} \right\}.$$

end

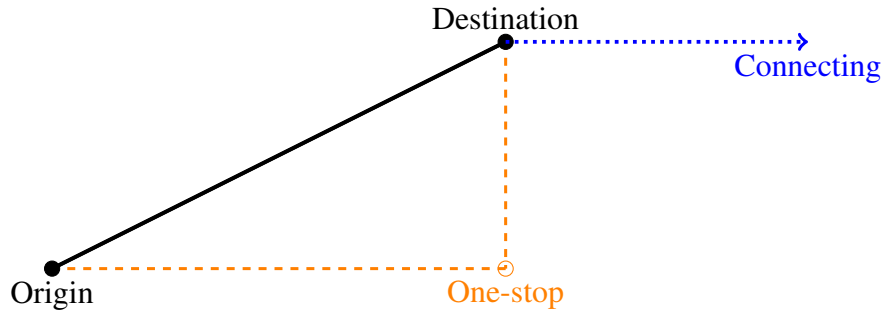
end

For $t = 1$ we continue to allocate the highest revenue fare class to the entire remaining capacity. Note that for this allocation rule, $b_k(t, d)$ is a function of time since the arrivals are changing over time. This policy can be computed for each time t and remaining capacity c, for all departure dates d and arrival rates λ.

B Route Selection

We use publicly available data to select markets to study. The DB1B data are provided by the Bureau of Transportation Statistics and contain a 10% sample of tickets sold. The DB1B does not include the date purchased nor the date traveled and is at the quarterly level. Because the DB1B data contain information solely for domestic markets, we limit our analysis to domestic markets as well. Furthermore, we use the air carrier's definition of markets to combine airports within some geographies.

Figure 11: Nonstop, One-stop and Connecting Traffic

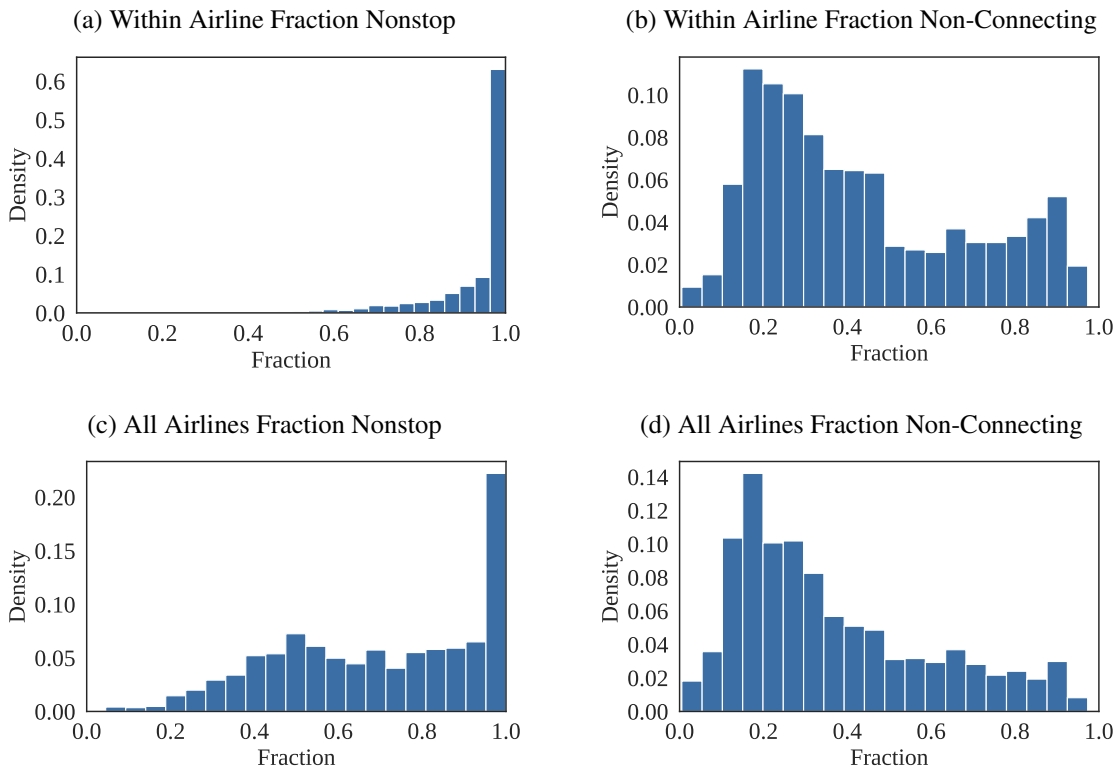


Note: We use the term nonstop to denote the sold black line, or passengers solely traveling between (Origin, Destination). Unless otherwise noted, we will use directional traffic, labeled $O \rightarrow D$. Non-directional traffic is specified as $O \longleftrightarrow D$. The blue, dashed lines represent passengers flying on $O \longleftrightarrow D$, but traveling to or from a different origin or destination. Finally, one-stop traffic are passengers flying on $O \longleftrightarrow D$, but through a connecting airport.

We consider two measures of traffic flows when selecting markets: traffic flying nonstop and traffic that is non-connecting. Both of these metrics are informative for measuring the substitutability of other flight options (one-stop, for example) as well as the diversity of tickets sold for the flights studied (connecting traffic). Figure 11 provides a graphical depiction of traffic flows in airline networks that we use to construct the statistics. We consider directional traffic flows from a potential origin and destination pair that is served nonstop by our air carrier. The first metric we calculate is the fraction of traffic flying from $O \rightarrow D$ nonstop versus one or more stops. This compares the solid black line to the dashed orange line. Second, we calculate the fraction of traffic flying from $O \rightarrow D$ versus $O \rightarrow D \rightarrow C$. This compares the solid black line to the dashed blue line.

Figure 12 presents summary distributions of the two metrics for the markets (ODs) we

Figure 12: Route Selection Using Bureau of Transportation Statistics Data



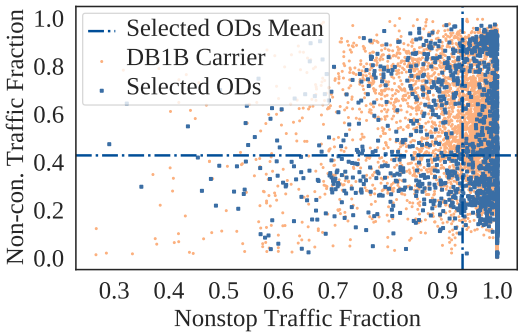
Note: Density plots over the fraction of nonstop traffic and the fraction of non-connecting traffic for the selected routes using DB1B data. "Within" means passengers flying on our air carrier. "Total" means all air carriers on a given origin-destination pair. Within nonstop and total nonstop coincide if our carrier is the only carrier flying nonstop.

select. In total, we select 407 ODs for departure dates between Q3:2018 and Q3:2019. The top row measures the fraction of nonstop and connecting traffic for tickets sold by our our carrier. The left plot shows that, conditional on the air carrier operating nonstop flights between OD, an overwhelming fraction of consumers purchase nonstop tickets instead of purchasing one-stop connecting flights. The right panel shows that fraction of consumers who are not connecting to other cities either before or after flying on segment OD. There is significant variation across markets, with the average being close to 50%.

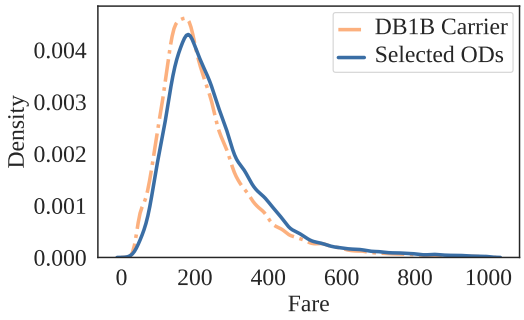
The bottom panel repeats the statistics but replaces the denominator of the fractions with the sum of traffic flows across all air carriers in the DB1B. Both distributions shift to the left because of existence of competitor connecting flights and sometimes direct com-

Figure 13: Inventory Allocation Adjustments and Lack of Sales

(a) DB1B OD Traffic Comparison



(b) DB1B OD Fare Comparison



Note: (a) A scatter plot of the fraction nonstop and fraction non-connecting for all origin-destination pairs served by our air carrier. The blue dots show selected markets; the orange dots show non-selected markets. (b) Kernel density plots of all fares in the DB1B data for our air carrier; the blue line shows the density for our selected markets.

petitor flights. In nearly 75% of the markets we study, our air carrier is the only firm providing nonstop service. Our structural analysis will only consider single carrier markets.

In Figure 13-(a), we show a scatter plot of the fraction of nonstop traffic and the fraction of non-connecting traffic for all origin-destination pairs offers by our air carrier in the DB1B. The orange dots depict routes non-selected markets and the blue dots show the selected markets. We see some dispersion in selected markets, however this is primarily on non-connecting traffic. An overwhelming fraction of the selected markets have high nonstop traffic, although this is true in the sample broadly. Essentially, conditional on the air carrier providing nonstop service, most passengers choose nonstop itineraries. In Figure 13-(b) we show the distribution of purchased fares in the DB1B for our carrier along with our selected markets. The distribution of prices for the selected sample are slightly shifted to the right, which makes sense since we primarily select markets where the air carrier is the only airline providing nonstop service.