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

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Abstract

Firms facing complex objectives often decompose the problems they face, delegating different parts of the decision to distinct sub-units. Using comprehensive data and internal models from a large U.S. airline, we establish that airline pricing is not well approximated by a model of the firm as a unitary decision-maker. We show that observed prices, however, can be rationalized by accounting for organizational structure and the decisions by departments that are tasked with supplying inputs to the observed pricing heuristic. Simulating the prices the firm would charge if it were a rational unitary decision-maker results in lower welfare than we estimate under observed practices. Finally, we discuss why counterfactual estimates of welfare and market power may be biased if prices are set through decomposition, but we instead assume that they are set by unitary decision-makers.

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1 Introduction

Firms face many complex decisions. Naturally, some are complex because they are ill-structured or arise only once. Other decisions can be complex even if they are cleanly structured and arise routinely. Confronted with a complex decision, a manager might consider two approaches. First, they might apply a heuristic that does not use all available information to solve the problem (e.g., Simon, 1956). Alternatively, they might decompose the problem, delegating different parts of the decision to different sub-units (e.g., Radner, 1993). However, this delegation of decision rights creates the potential for coordination failures, and, if sub-units also rely on heuristics, this may cause decisions to differ significantly from those commonly used to study firm behavior. There may also be significant consequences for efficiency and welfare.

In this paper, we demonstrate the importance of organizational structure and the use of heuristics in understanding firm pricing behavior. Using granular data and internal models from a large U.S. airline, we show that pricing is subject to important biases, including: relying on a heuristic that does not internalize product substitution of any kind, using persistently biased forecasts, and pricing on the inelastic side of internally estimated demand curves.[1] However, we show that prices can be explained by accounting for organizational structure and the decisions made by the multiple departments that are tasked with supplying inputs to the observed pricing heuristic. Given other departments' heuristic inputs, providing biased inputs is revenue maximizing for the firm. In other words, department managers choose inputs in a boundedly rational way given their delegated decision rights and the complex interactions of department input decisions in the pricing heuristic (Simon, 1956, 1962). There are substantial welfare consequences from prices being set through such decomposed decision-making. Simulating the prices the firm would charge if it were a rational unitary decision-maker

[1]We use the term heuristic instead of algorithm throughout to emphasize that the heuristic used by the firm does not solve an economic model.

results in lower welfare than we estimate under observed practices due to increased price targeting. We discuss why counterfactual estimates of welfare and market power may be biased if we assume prices are set by a unitary rational decision-maker when they are in fact set through decomposition.

Following deregulation, airlines adopted pricing heuristics that relied on decentralized decision-making by individual departments.[2] In the observed organizational structure, the "network planning department" decides where to fly and assigns initial capacities. Given the network, the "pricing department" designs itineraries and chooses a menu of discrete fares that consumers may face. Finally, the "revenue management department" (RM) is responsible for estimating demand, developing flight forecasts, and monitoring flight-level performance. These inputs are then given to the observed pricing heuristic that decides how many seats it is willing to sell at each fare level. For a fictional example, the network planning department might decide to fly twice a day from London to Paris, once in the morning and once in the afternoon, and sets the size of the plane for each flight. The pricing department might decide that there are three economy fare levels, say \$200, \$150, and \$100, for each flight. The revenue management department, using an estimate of the demand curve for each flight, develops a demand forecast for each of the three fare values. These inputs—the capacity decisions, the fare menus, and the forecasts—are given to the heuristic, which allocates remaining seats to each fare.

While we directly observe the separation of pricing responsibilities for the large U.S. airline that we study, we confirm that this organizational structure is used also used widely by other firms solving complex pricing problems. Analyzing online job listings and professional network profiles, we show that some ultra low-cost carriers, recently founded airlines, and all major airlines maintain separate pricing and RM

[2] We do not observe decisions being delegated to a single subordinate (e.g., Aghion and Tirole, 1997). The organizational structure also possesses similarities to more recent theoretical work in organizational economics that analyze decentralized decision-making (e.g., Alonso, Dessein, and Matouschek, 2008; Rantakari, 2008; Dessein, Galeotti, and Santos, 2016).

departments. Moreover, cruises, hotels, car rental, and ride share companies have the same organizational structure and department responsibilities. We believe that our approach, analysis, and results apply more widely across many important sectors of the economy.

Our study leverages comprehensive data from a large U.S. airline. In addition to observing daily prices and quantities, we observe all department decisions, including capacity choices, fare decisions, the internal demand model, demand estimates, flight-level forecasts, and the pricing heuristics's exact design (code). We also observe all consumer interactions (clicks) on the airline's website. Our sample covers 300,000 flights and 470 domestic routes over two years.

We document three important facts using the data and internal models used by the firm. First, we describe the pricing heuristic used by the firm and show that observed pricing rules differ from the empirical literature that studies pricing through the lens of optimal dynamic unitary decision-making.[3] In particular, the heuristic does not solve a dynamic program. Instead, it is myopic and considers the same static allocation problem every day. It abstracts from all forms of substitution, including across cabins within a flight, flights within a day, departure dates, and competitor options.[4] Every flight is optimized using the same heuristic, regardless of market structure.

Second, we show that department input decisions are biased and subject to miscoordination. For example, the RM department relies on the same single-product demand model for all routes, despite significant differences in competition and the number of flights per day. We show that departments do not internalize all of the decisions made by other departments, leading to input decisions that are "incompatible." We show that the pricing department frequently chooses fares that are on the inelastic side of the RM department's demand model. We explain why this leads the heuristic to frequently

[3]For examples, see Sweeting (2012); Cho, Lee, Rust, and Yu (2018); Williams (2022); Aryal, Murry, and Williams (2022); Pan and Wang (2022).

[4]This can affect what inferences can be made about market conditions. For related theoretical work, see, e.g., Bohren (2016) and Heidhues, Kőszegi, and Strack (2018).

offer consumers “inelastic” prices.

Third, we show that departments manipulate the inputs they supply to the pricing heuristic. These actions are consistent with manipulating information in behavioral theories of the firm (Cyert and March, 1963). For example, we show that RM analysts inflate the demand model, causing 93% of flights to be over-forecasted when supplied to the heuristic. These actions are consistent with several potential behavioral explanations, including overconfidence and mis-reaction to information (e.g. Camerer and Lovallo, 1999; Bordalo, Gennaioli, Ma, and Shleifer, 2020; Ma, Ropele, Sraer, and Thesmar, 2020). These actions are also consistent with using a workaround or “kludge” (Ely, 2011) to address a known issue with the heuristic—that it can deflate opportunity costs of capacity due to its design (Wollmer, 1992; Brumelle and McGill, 1993; Cooper, Homem-de Mello, and Kleywegt, 2006).[5] We estimate the effect of analysts over-forecasting demand reduces the percentage of flights that are priced on the inelastic side of the internal demand model by up to 60%.[6]

These facts are central to how we study delegated decision-making and the use of a pricing heuristic. While we observe a great deal about pricing decisions, we do not directly observe consumer preferences. We do not use the RM department’s single-product demand model to inform consumer preferences due to its inflexibility in capturing demand heterogeneity within and across routes, e.g., the model assumes that demand does not depend on the departure date. Instead, we estimate a flexible demand model for air travel using a recently proposed methodology (Hortaçsu, Natan, Parsley, Schwieg, and Williams, 2023). We use these estimates to simulate demand and measure welfare in counterfactuals.

In the demand model, “leisure” and “business” travelers arrive according to time-varying Poisson distributions. Conditional on arrival, consumers solve a standard dis-

[5] According to Ely (2011), “A kludge is a marginal adaptation that compensates for, but does not eliminate, fundamental design inefficiencies.”

[6] There may also be competitive reasons to bias forecasts. Berman and Heller (2020) present a theory on why biases can persist, including underestimating price elasticities, in a model of competition.

crete choice problem. We provide new descriptive evidence that supports our modeling assumptions. Our model allows for endogenous prices, and we address the challenge of separably identifying preferences from aggregate demand uncertainty by leveraging arrivals and bookings data. We show that our demand estimates are robust to both the choice of instruments and the choice of hyperparameters that account for unobserved arrivals. In total, we estimate 235,000 demand parameters across 140 routes. We find substantial variation in willingness to pay within and across routes. We estimate that business consumers are on average five times less price sensitive than leisure consumers. Average elasticities are -1.1 (SD=0.6).

Next, we present our model of supply. Fully endogenizing department decisions is difficult because we do not observe incentive structures. Moreover, departments make many decisions—50 million department inputs are provided to the heuristic each day for the routes in our sample. We simplify our analysis by considering specific unilateral department adjustments to observed inputs and assume that department incentives are aligned with the firm. In addition, we do not endogenize capacity decisions. Later, we discuss implications for our results. We compare market outcomes using observed inputs supplied to the heuristic to unilateral deviations in one department's decisions, holding all other decisions fixed. For deviations, we consider the scenario where the pricing department removes fares that guarantee that the heuristic will never offer "inelastic" prices. We also consider the scenario where the RM department reduces the persistent upward bias in their demand forecasts.

We present two main findings. First, we show that these unilateral deviations do not increase revenues. Among the deviations considered, miscoordinated and biased inputs are revenue maximizing for the firm. This result is economically important as it establishes that pricing biases can be explained by accounting for organizational structure and the use of simplifying heuristics, whereas existing work has attributed bias to behavioral frictions, mistakes (e.g., Levitt, 2016; DellaVigna and Gentzkow, 2019;

Dubé and Misra, 2021) or a misalignment of incentives within the organization (Atkin, Chaudhry, Chaudry, Khandelwal, and Verhoogen, 2017; Sacarny, 2018). Although we find no revenue-increasing unilateral deviations from decreasing input bias, we find small gains under extreme biases, e.g., a 1% revenue increase if the RM department overstated their forecasts by 100%.

Our second main finding is that observed prices are inconsistent with a model of the firm as a unitary, rational decision-maker. More precisely, given our demand estimates, we simulate the prices the firm would charge if it solved a dynamic program as a single entity. We limit our analysis to a subset of routes due to the intractability of solving dynamic programs for the airline's larger routes. We find that observed prices differ substantially from those implied under dynamic pricing. Dynamic pricing results in increased price targeting and lower welfare (by 9%) compared to prices set under observed practices. If the firm solved a dynamic program as a unitary decision-maker, leisure consumers would benefit, and business consumers would be made worse off.

Finally, we review our findings and discuss how our insights can be used to study firm pricing more broadly. We provide novel empirical evidence using internal data and models from a large US firm to highlight the complexity, constraints (Siggelkow, 2001), and consequential simplifications imposed in pricing decisions. We contribute to a small but growing literature on the consequences of firm behavior under biased beliefs or bounded rationality (e.g., Cho and Rust, 2010; Brown, Camerer, and Lovallo, 2013; Goldfarb and Xiao, 2011, 2016; Aguirregabiria and Magesan, 2020). We offer the first direct empirical quantification on the differences between internal firm pricing practices and what Rust (2019) describes as the questionable yet maintained assumption that firms behave "as if" they have solved the dynamic problems they face. We highlight that welfare estimates and measurements of market power are sensitive to the assumptions to how we model supply. In our context, the firm does not internalize static (e.g., product substitution) and dynamic (e.g., scarcity) opportunity costs as commonly assumed in empirical work (for an overview, see Aguirregabiria, Collard-Wexler, and Ryan, 2021). If prices are generally set through decomposition and involve heuristics—as we observe at a sophisticated firm—failing to account for coordination failures and consequential simplifications made in practice can lead to misinterpreting observed outcomes and incorrectly simulating counterfactuals.

The paper is organized as follows. In Section 2, we discuss industry pricing practices and detail the pricing heuristic used by the firm. We discuss the data in Section 3 and pricing biases in Section 4. We present the demand model, estimation details, and parameter estimates in Section 5. We investigate department decisions in Section 6. We consider dynamic pricing in Section 7. The conclusion follows.

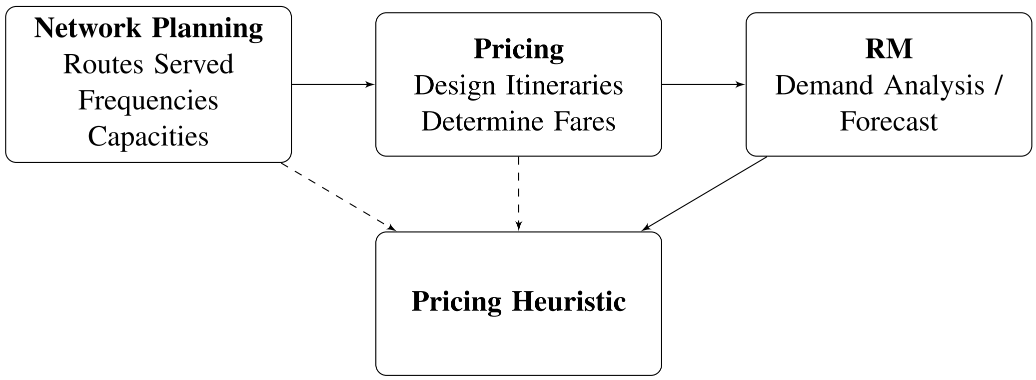
2 Organizational Structure and Pricing Heuristic

We study the U.S. airline industry, which directly supports over 2.2 million jobs and contributes over $267 billion to the U.S. economy (IATA, 2019). We briefly describe airline pricing practices. Vinod (2021) provides a detailed, historical account.

Prior to deregulation of the airline industry, the networks and fares of airlines were federally controlled. At that time, pricing was not automated, and airlines physically posted the fares they offered. Post-deregulation, competition intensified, which resulted in airlines lowering fares, particularly for consumers who shopped early. These were the first advance purchase (AP) fares that are now common in advance purchase markets.

In 1972, the UK-based airline BOAC developed the first tractable inventory management system that controlled how many discounted fares to offer based on expected demand. American Airlines further developed this optimization tool as computing power increased (Vinod, 2021). The adoption of inventory management tools resulted in a bifurcation of pricing responsibilities, with one department designing the itineraries consumers can purchase and another department monitoring and managing flight-level performance.

Figure 1: Division Responsibilities at all Airlines



Note: Key departments, responsibilities, and decision-making process at all airlines. The dashed arrows show the flow of information that can be leveraged by departments. The solid arrows show the flow of decisions, i.e., decisions are based to the pricing heuristic.

Figure 1 depicts the organizational structure we study. First, the network planning department decides routes served, flight frequencies, and capacities. We do not endogenize these decisions in our analysis and discuss their implications in Section 7. The schedule is passed to the pricing department, which is tasked with designing the itineraries that can be purchased. This includes choosing a discrete menu of fares and fare restrictions, including any AP requirements, for every itinerary.[7] AP requirements establish the minimum price that can be offered at any point in time and are effective for segmenting customer demand across time (McGill and Van Ryzin, 1999).[8] The pricing department also gathers and interprets competitor fares and initiates/responds to industry-level changes, e.g., implementing a fuel surcharge. These fare choices are given to the RM department, which is responsible for demand analysis, developing and updating flight-level forecasts, and merging all departments' inputs into the pric-

[7] Advance purchase (AP) fares are common at 7, 14, and 21 days before departure.

[8] The pricing department decides fares that cover different classes of service, connecting options, blackout dates, etc. Each fare has dozens of characteristics that can be adjusted. The coarsest level of a fare is its fare class, e.g., discounted economy versus full-fare economy.

ing heuristic.

While our study is limited to a single airline, we verify that this organizational structure is used widely by firms in several important industries. In Tables 10 and 11 in Appendix C, we document excerpts of job postings and professional network profiles that show all major airlines, including legacy carriers, low-cost carriers, and start-up airlines maintain separate pricing and RM departments. We also find that the observed organizational structure can be found in car rentals, hotels, cruises, trains, and even at the rideshare service Uber. Therefore, we believe our insights likely apply broadly to firms that engage in dynamic pricing.

2.1 Pricing Heuristic Details and the Effects of Input Decisions

All department decisions—the schedule/capacity constraint set by the network planning department, the fare menu decisions of the pricing department, and the demand analysis and flight-level forecasts made by the RM department—are inputs to the pricing heuristic. A novel feature of our study is that we observe the heuristic used by the firm. This allows us to simulate market outcomes based on observed practices and permits us to separate the effects of individual department decisions in counterfactuals. We describe the heuristic's basic properties here. We provide psuedo-code, a simple example, and additional details in Appendix A.

The airline uses a heuristic called Expected Marginal Seat Revenue-b, or EMSRb (Belobaba, 1987).[9] EMSRb differs from dynamic pricing models in several important ways, including that it considers a sequence of static problems. It does not choose a price, rather, it allocates how many seats it is willing to sell at each fare (see Dana (1999), for related theoretical work). The lowest-available fare (LAF), or the price consumers readily see when shopping for flights, is the least expensive fare to which

[9]The heuristic was proposed by Peter Belobaba in his PhD thesis. There are multiple forms of EMSR. EMSRa differs from EMSRb in how remaining inventory is aggregated. We verify the version used by the airline by inspecting its code.

the heuristic allocates inventory. Throughout, we use "price" to refer to the lowest-available fare, and "fares" to refer to pricing department's input to the heuristic. The heuristic sets booking limits to segment demand. For example, if demand at higher prices is expected to be high, it will restrict the inventory it allocates to less expensive fares. Code revisions confirm the heuristic has been used at the firm for over 25 years.

To better understand the heuristic, imagine that there are two types of customers, high and low willingness to pay (WTP) customers. Low WTP consumers are willing to pay $p_L < p_H$. The heuristic assumes that all low WTP consumers will arrive first, or more generally, that consumers will arrive in increasing order of willingness to pay. It segments demand by calculating a protection level (x) that reserves capacity for high WTP customers. With a capacity C, the remaining $C-x$ units are offered to low WTP customers. What determines this threshold? The heuristic uses Littlewood's Rule, $p_H \cdot (1-\Pr(Q_H \leq x)) = p_L$, which can be solved for x.[10] This sets the opportunity cost of saving a seat for high WTP consumers equal to the value of selling it today at p_L.[11]

In practice, EMSRb is implemented in a two-stage process. First, aggregate demand is calculated. This is the sum of a flight's forecasted demand remaining over time, evaluated at the pricing department's fare choices. Second, it then recursively uses Littlewood's rule to set protection levels for each fare (the xs).[12] Because Littlewood's Rule requires two fares, EMSRb collapses the inverse demand curve above a given fare into a single statistic as it allocates capacity (see Appendix A for an illustrative example and mathematical expression). This simplification makes it a heuristic—its solution does not correspond to solving an economic problem. However, its assumptions allow it to re-optimize remaining inventory easily whereas solving dynamic programs at scale is very difficult due to the curse of dimensionality.[13]

[10]The idea was developed by BOAC airline employee Ken Littlewood.

[11]Note that with two fares and two consumer segments (arriving over time as assumed), Littlewood's Rule is equivalent to solving a constrained revenue maximization problem.

[12]This characterizes how the airline prices tickets. The heuristic does not consider ancillary revenue, including baggage fees, upgrade charges, etc., when it makes its decisions. Fares are not personalized.

[13]To illustrate this point, imagine that there are four flights a day. The flights are offered for sale

The heuristic also makes a number of additional consequential simplifications. For example, it does internalize the existence of any substitutes. Observing identical prices for flights offered by the airline within a day or across competitors is made possible by the pricing department's actions, but it is not enforced by the heuristic.[14] An important limitation of our study is that although we model fare decisions, we do not study potential competitor responses to these decisions. Offering simple fare structures may be useful for competitive reasons (Cyert, Kumar, and Williams, 1995), whereas our analysis focuses on how it can be used for market segmentation.

Decomposing the problem across departments can create challenges because all department inputs can affect how the heuristic allocates remaining inventory. For example, suppose that the pricing department wants to run a sale (or match a competitor) by adding a low fare to the menu. This fare decision is fed through the RM department's demand models to create forecasts. If the forecasts are such that the heuristic protects a significant amount of inventory at higher fares, it may not allocate any inventory to the low, sale fare. That is, the RM department's demand input (or network planning input) can offset the pricing department's intentions. Consequently, unilateral department actions may lead to limited change (Milgrom and Roberts, 1990, 1995).

3 Data and Summary Analysis

We use comprehensive data from a large international airline based in the United States. We first describe the routes we study. We then introduce and summarize the data. We provide descriptive evidence on department decisions in Section 4.

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for 100 days, and each flight has 200 seats. The dimensionality of this single problem is 160 billion. Accounting for connecting demand makes the problem intractable.

[14]In the case of substitute flights at the airline, fare menus vary by departure date but not across flights within the same day. For routes with exactly two daily frequencies, we find that both flights have identical prices 60% of the time. In the case of substitute flights at other airlines, the pricing department may choose a similar fare menu to its competitors. Betancourt, Hortaçsu, Öry, and Williams (2023) document similar price matching in markets with competition.

3.1 Route Selection

We select a subset of routes to study because of data size constraints. We apply the selection criteria below to the publicly available DB1B data provided by the Bureau of Transportation Statistics.[15] Using data from the first three quarters of 2018, we filter routes (origin-destination pairs) based on the following criteria:

i) Combine nearby airports to create "city codes;"

ii) Remove routes where over 10% of passengers fly on carriers that do not make their tickets available on third-party websites;

iii) Retain routes where at least 25% of passengers fly on our airline;

iv) Retain routes where at least 750 passengers fly quarterly;

v) Remove routes where fewer than 500 passengers fly nonstop quarterly.

Selection criteria (i) ensures that our market definition covers relevant airport substitution. Our groupings follow existing work, e.g., Berry (1992).[16] Criteria (ii) removes routes where competitor information may not be available to the airline[17]; (iii) ensures that our data contains meaningful amount of traffic on our airline, (iv) eliminates small routes, and (v) ensures that markets have meaningful nonstop traffic.

We perform these operations for all three quarters separately and take the union of routes. Given the resulting set, we sort routes based on the fraction of passengers flying nonstop (decreasing). We select the first 470 routes from this list. Our selection criteria result in a diverse set of routes in terms of competition, capacities, flight frequencies, and traffic flows. The sample contains large routes between major cities as well as routes from metropolitan areas to small cities. For 60% of routes in the sample, the airline faces no direct nonstop competition. For the remaining 40% of routes in the

[15]The DB1B contain a 10% sample of domestic tickets sold, however, the data do not include key details, including when tickets were purchased, the date consumers traveled, and the flights involved. Therefore, we use the DB1B solely for route selection.

[16]The groupings are: (HOU, IAH); (DFW, DAL); (BWI, DCA, IAD); (MDW, ORD); (EWR, JFK, LGA); (LAX, LGB, ONT, SNA, BUR, SBA); (SFO, OAK, SJC).

[17]We do not study strategic interactions—see Betancourt, Hortaçsu, Öry, and Williams (2023).

sample, the number of nonstop competitors ranges from one to seven. We obtained data over two years and created a sample of flights that departed between August 1, 2018 to August 31, 2019.[18]

In Online Appendix B, we present more detailed summaries of the routes studied and compare route characteristics in our sample to all U.S. domestic travel.

3.2 Data Overview

We combine (1) bookings, (2) inventory, (3) search, (4) fares, and (5) forecasting data. We describe each data set, identifying key variables used. In Appendix C.2, we provide a synthesized observation for each table.

(1) Bookings data: We observe all tickets purchased, regardless of booking channel, e.g., the airline's website, travel agency, etc. The data are analogous to what a consumer observes after booking a flight, e.g., the routing, flight numbers, departure date(s) and time(s), fare paid, number of passengers, and the booking channel.

(2) Inventory data: The inventory data contain the daily decisions made by the pricing heuristic. For every flight, each day before departure, the data record the number of seats the airline is willing to sell at each price level. Also included in the data set is the departure and arrival times, the actual capacity, the authorized capacity in case overselling is allowed, and the heuristic's calculated opportunity cost of capacity, which is its approximation of the difference in expected revenues if the flight had one fewer seat. In addition, we observe the pricing heuristic's code.

(3) Search data: We observe all "clicks" on the airline's website for two years. The search data contain over one billion data points which track how consumers engage with the website. We extract all entries related to the action of submitting a search query, which we use to measure market sizes (see Appendix C.3 for our cleaning procedure).

[18] Data transfer began in 2019, before the release of each quarter of the 2019 DB1B.

(4) Fare data: The fare data contain the pricing department's decisions. Fares vary by route and departure date, but not across flights within a departure date. Many departure dates typically share the same fare menu. A fare denotes a price and ticket restrictions, including any advance purchase requirements. Each menu contains roughly a dozen fares, and analysts may adjust individual fares over time. We provide an actual fare menu for a European airline in Table 16 in Appendix C.2.

(5) Forecasting data: The RM department forecasts demand based on short-run demand estimates. We use "demand model" to denote the observed, baseline demand model and "demand forecasts" to denote the demand model's predictions after analyst adjustments. Analysts may adjust the demand model based on the performance of recently departed flights, an updated prediction regarding seasonality, or other information. The demand forecasts are still demand curves, i.e., quantity demanded for a given price. The RM department maintains separate models/forecasts for "business" and "leisure" travelers. We observe the demand model, internal demand estimates, all analyst adjustments, and the resulting flight forecasts. Forecasts are maintained from the time a flight is initially scheduled all the way through the departure date. Adjustments to the forecasts incorporated in seven day intervals (see Figure 2).

We observe the anonymized identities of the pricing and RM analysts responsible for the routes we study.

3.3 Summary Analysis

Table 1 provides a basic summary of the 300,000 flights in our sample. We focus on the last 120 days before departure due to the overwhelming sparsity of search and sales observations earlier in the booking horizon.

Average prices in our sample are \$198, with large dispersion across routes and over time. Typically, prices for a particular flight adjust nine times. Many fare adjustments occur at specified times, such as after expiration of AP opportunities (see Figure 2-a).

Table 1: Summary Statistics

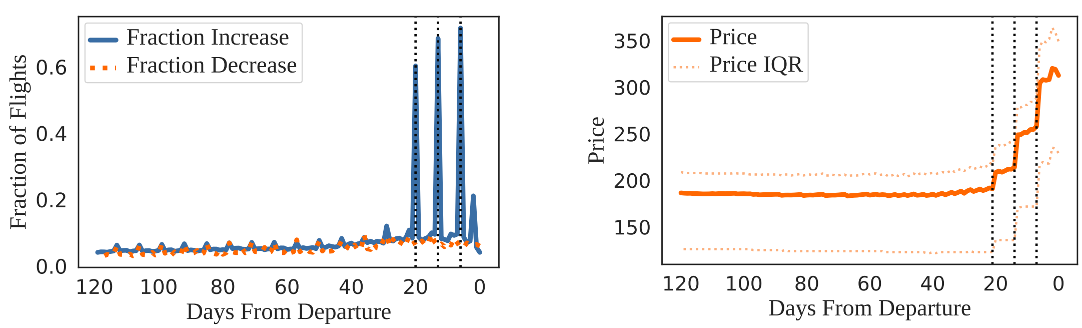
Variable	Mean	Std. Dev.	Median	5th pctile	95th pctile
Prices					
One-Way Price ($)	197.8	127.2	162.2	87.0	404.1
Num. Price Changes	9.3	4.1	9.0	3.0	17.0
Price Change ($), Cond. on Inc.	49.8	71.3	31.2	2.2	161.2
Price Change ($), Cond. on Dec.	-52.0	73.3	-32.2	-168.8	-4.3
Booking					
Booking Rate-OD	0.2	0.7	0.0	0.0	1.0
Booking Rate-All	0.6	1.4	0.0	0.0	3.0
Ending LF (%)	81.8	21.9	90.0	35.8	102.0
Searches					
Search Rate	1.8	4.8	0.0	0.0	9.0

Summary statistics for the data sample. The booking rates are for non-award, direct travel on nonstop flights and for all traffic on nonstop flights (including passengers who connect onward), respectively. The number of passengers denotes the number of passengers per booking. Load factor includes all bookings, including award and connecting itineraries. The search rate is for origin-destination queries at the daily level.

Over 60% of all price adjustments occur outside these time windows. In Figure 2-(b), we plot average prices over time. Prices increase by over 70% in 120 days. Prices increase even for flights with low realized demand due to AP discounts expiring.

Figure 2: Price Time Series

(a) Fraction of Price Changes (b) Prices



Note: Fraction of price changes and average prices by day before departure. Also included is the IQR across prices.

The booking rate (quantity per flight-day) is low, and the percentage of zero sales is 89%. Importantly, the highest booking rates occur when prices are the highest, within the last 7 days before departure. The average load factor (percentage of seats occupied) at departure is 82%. Although over 5% of flights eventually oversell, we abstract from this possibility because we do not observe denied boarding/no show information. We use the flight's authorized capacity in our analysis because that is the capacity used by the heuristic uses when it allocates remaining inventory. The median number of seats the RM department is willing to oversell in our sample is one.

3.4 Motivating Evidence on Demand

We provide new descriptive evidence to motivate many of our modeling assumptions. The bookings data suggest that unit demand is a reasonable assumption. The average number of passengers per booking is 1.3, and the median is 1. By default, consumers see the lowest-available fare (LAF). Moreover, 91% of consumers purchase the LAF.[19] Therefore, we model consumers purchasing tickets at the LAF only.[20]

We do not endogenize capacity choice as only 2% of flights ever experience a change in capacity. Most changes occur more than 100 days before the departure date. 30% occur within 48 hours of departure (due to operational issues).

We adopt a two-type consumer model, corresponding to "leisure" and "business" travelers, as is common in the literature.[21] This is also how the RM department models demand. The labels "leisure" and "business" are mechanically linked to attributes of the ticket, e.g., the number of days before departure it was booked and are not attached to traveler characteristics, e.g., passenger status or travel purpose.

We assume a static discrete choice model based on search patterns that we document.[22] We "daisychain" the clickstream data by linking search activity across time

[19] Consumers with the highest statuses are the most likely to buy tickets at fare classes above the LAF. This finding complements Orhun, Guo, and Hagemann (2022), who show that loyal consumers tend to fly longer itineraries than necessary in order to obtain status at an airline whose loyalty program is mileage based.

[20] Special fares, such as corporate or government discounts, are rare in the routes studied.

[21] For examples, see Berry, Carnall, and Spiller (2006), Berry and Jia (2010), Lazarev (2013), Aryal, Murry, and Williams (2022), and Williams (2022). This specification has also been used in other contexts, e.g., Besanko, Dubé, and Gupta (2003)

[22] All the cited literature in footnote 21 assume short-lived buyers with the exception of Lazarev

using cookies (see Appendix C.3) and establish the following facts:

i) 82% of customers search a single departure date,[23]

ii) 90% of consumers complete all their search activity in a single day,

iii) Among the 10% of consumers that search the same departure date over time, 20% ever observe a lower fare for at least one flight in later searches,[24]

iv) 62% of consumers would have received a lower price if they shopped a week earlier; 8% would have benefited from delaying their purchasing decision.

We note that while many of our assumptions are also made in the RM department's demand model (short-lived buyers, no substitution across departure dates and days before departure), these assumptions can affect estimated demand elasticities. In particular, Hendel and Nevo (2006) show in the retailing context without capacity constraints that assuming short-lived buyers when in fact consumers are forward-looking can lead to overstating consumer price sensitivity. That is, it is possible that demand may be more inelastic than our estimates suggest. Moreover, the extent to which consumers are flexible across departure dates and routes creates a product variety benefit that the pricing heuristic does not exploit.

4 Pricing Biases in Airline Markets

Using the firm's data and internal models, we provide examples of pricing biases that affect all flights, regardless of market structure.

(2013), who assumes buyers know their future preferences, but are uncertain if they can fly, and prices are deterministic.

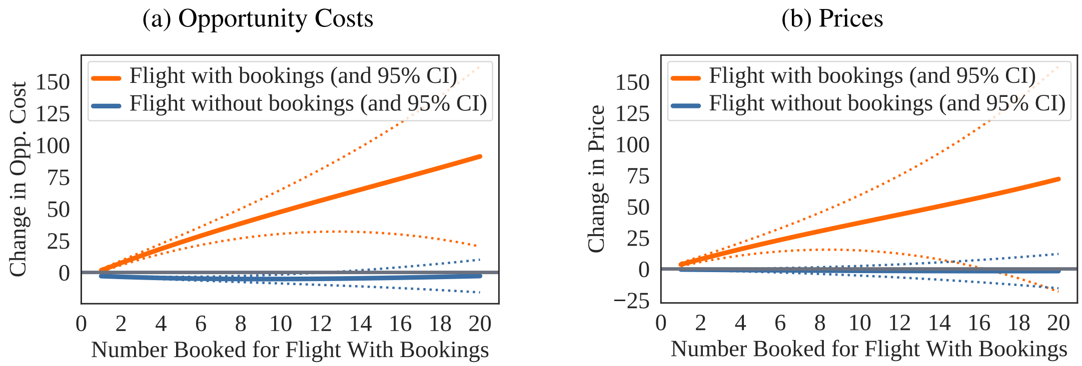
[23] Among the remaining 18%, the average time lag between these searches is 45 days, suggesting that consumers may be searches for different trips entirely.

[24] Our estimates of consumer waiting is lower than estimates by Li, Granados, and Netessine (2014) that are model derived without access to search data.

4.1 Heuristic Bias

The pricing heuristic used by the firm (see Section 2) greatly reduces computational burden because it avoids solving a dynamic program. However, this also makes the heuristic dynamically inconsistent as it does not internalize that it will revisit its decisions every day. Another consequence of its design is that it does not account for cross-price elasticities of any kind, including across cabins within a flight, other flight options, and competitors. All flights, regardless of market structure, flight frequency, etc., are priced using the same single-product heuristic.

Figure 3: Opportunity Cost and Price Response to Bookings with Multiple Flights



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

The heuristic does not even indirectly react to demand realizations of substitute flights. This precludes direct responses to competitors. In Figure 3-(a), we plot the average change in opportunity costs, as reported by the heuristic, for the flights that receive bookings and for the flights that do not receive bookings (the substitute option) using a polynomial regression (of degree four).[25] In dynamic pricing models (see, e.g. Gallego and Van Ryzin, 1994; Betancourt, Hortaçsu, Öry, and Williams, 2023),

[25] For this exercise, we select observations based on the following criteria: (i) the firm offers two flights a day; (ii) we include periods where demand is not being reforecasted (the observed spikes in Figure 4); (iii) one flight receives bookings and the other flight does not, and (iv) the bookings do not cause a sell out.

a decrease in remaining capacity affects optimal prices for all products. Figure 3-(a) confirms opportunity costs for the substitute flight are unaffected by bookings on the focal flight. Because opportunity costs define how the heuristic allocates remaining capacity, we find that there is no price response (see panel b).

4.2 The Presence of Pricing Frictions

The use of discrete fare menus creates pricing frictions, which we directly measure using the firm's data. In Figure 4-(a), we plot the fraction of flights that experience changes in price or opportunity costs (OCs) as reported by the heuristic over time. Opportunity costs change much more frequently than the prices consumers face. The noticeable 7-day spikes in the figure reflect the fact that the RM department implements analyst adjustments in fixed, 7-day intervals before departure. Analyst adjustments lead to a larger fraction of flights experiencing a change in OCs and prices at those times.

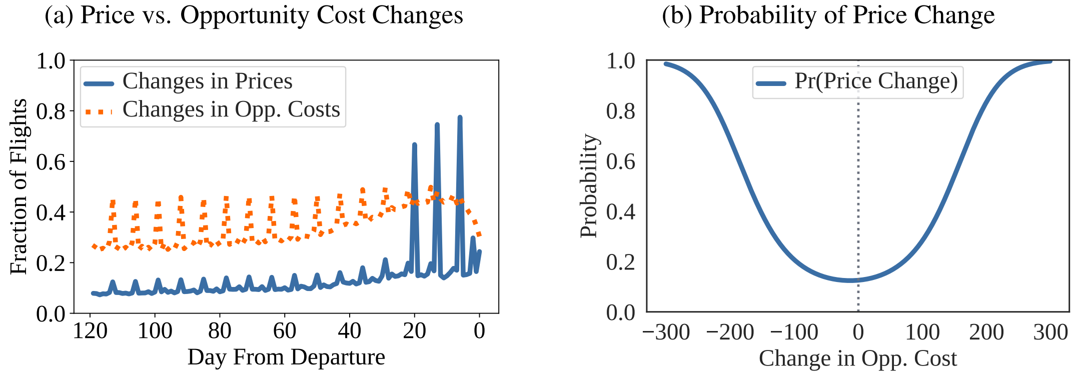
In Figure 4-(b), we plot the fitted values of a logistic regression with a flexible polynomial expansion of degree four of the change in OCs on an indicator function of the price changing. We find that changes in OCs exceeding \$100 only lead to a change in the price with a 20% probability.

4.3 Allocating Inventory to Fares that do not Exist

All department decisions affect the heuristic's choices, and we show that the process of combining inputs is subject to department "miscoordination." More specifically, we observe situations in which the fares used by the heuristic differ from those decided by the pricing department. This is possible if the RM department has not incorporated all fare changes made by the pricing department (they also manage all inputs).

Comparing the pricing department's decisions to those used within the RM sys-

Figure 4: Price Adjustments in Response to Opportunity Cost Changes



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

tems, we observe inventory allocations to fares that do not exist in 11.7% of the data sample. In these instances, the heuristic allocates seats based on fares that consumers cannot transact at. This affects inventory allocations. However, when consumers shop for flights on the firm's website and all other booking channels, they observe the actual fare on the pricing department's fare menus.

This form of miscoordination may arise because combining high-dimensional, frequently updated inputs across multiple IT systems which interface both internally and externally is a difficult process. Although we do not directly study this form of miscoordination in our counterfactuals, we do simulate market outcomes under alternative fare menus, which implicitly removes this bias.

4.4 Fares on the Inelastic Side of Demand Curves

Another form of miscoordination that we observe is that the pricing department often files fares that are too low according to the RM department's internal demand model. Although this would be inconsequential if the pricing heuristic solved an economic model—it would never offer a fare on the inelastic side of demand—in practice, the heuristic may not prevent "inelastic prices" from being offered to consumers. When capacity is not sufficiently constrained, the heuristic may not protect enough seats at higher fares so that inventory is allocated to fares on the inelastic side of the RM department's demand model. This can occur even if the more expensive, revenue maximizing fare is in the fare menu.

To quantify this form of miscoordination, we use the RM department's continuous and differentiable demand model, $Q(p)$. All domestic routes rely on one of six demand specifications (sets of parameters), which allow demand to vary by time until departure and day of the week.[26] Using the model, we calculate the elasticity of demand, $e(p)$, and plug in the lowest fare filed by the pricing department. We find that if the heuristic allocated seats to these fares, consumer demand would be inelastic according to the RM department's demand model in 98% of the sample.[27]

4.5 Using Persistently Biased Forecasts

Finally, we find evidence that RM analysts adjust the underlying demand model in a persistent way—they inflate it, which leads a systematic overprediction of demand as an input to the heuristic. We find that this is nearly always accommodated by scaling up all routes' demand predictions simultaneously by a common factor.

In Figure 5, we plot the average forecast bias by week before departure. We calculate the forecast bias for a particular week before departure as

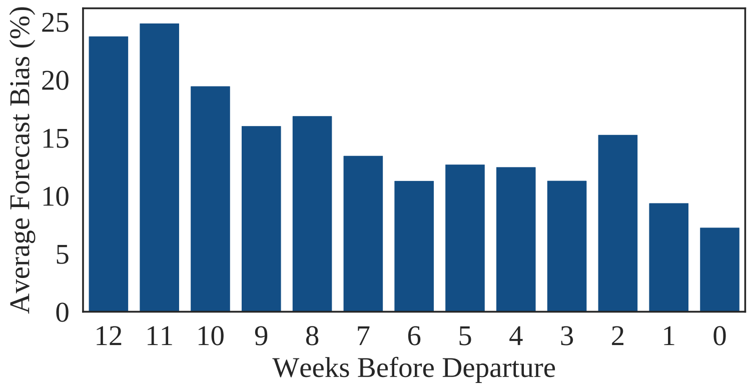
$$\text{Forecast Bias} := 100 \cdot \frac{\sum_{j,d,t} \mathrm{EQ}_{j,d,t}(p_{j,d,t}) - \sum_{j,d,t} \mathrm{Q}_{j,d,t}(p_{j,d,t})}{\sum_{j,d,t} \mathrm{Q}_{j,d,t}(p_{j,d,t})},$$

which is the difference between forecasted and realized demand over realized demand,

[26]The demand model does not accommodate departure date parameters. In addition, one set of demand parameters may be applied across dissimilar markets. For example, one set of demand parameters is used for a small single-carrier route but also for the route with the largest number of daily frequencies and nonstop competition.

[27]We note that these fares are not potential "sale" fares, as sale fares have special, observable attributes and are only present for short periods of time.

Figure 5: Forecast Bias by Week Before Departure



Note: Forecast bias is calculated by comparing the sum of expected bookings for each flight (and price) to realized bookings, by week before departure.

at observed prices. We sum over all flights (j), departure dates (d), and days before departure (t), for a given week. We find that the average forecast bias ranges between 25% and 7% by week before departure. 93% of flights are initially overforecasted. Interestingly, we find that routes with nonstop competitors feature larger forecasting bias compared to single-carrier routes on average. This may be due to the increased complexities of using single-product demand model in markets with competition.

While observing persistently biased forecasts is consistent with several behavioral biases, including overconfidence/overoptimism (Camerer and Lovallo, 1999; Huffman, Raymond, and Shvets, 2022) and over- and under-reaction to information (Bordalo, Gennaioli, Ma, and Shleifer, 2020), research in operations has shown that the pricing heuristic used by the firm may result in "underpricing" due to the heuristic's assumptions (Wollmer, 1992; Brumelle and McGill, 1993; Cooper, Homem-de Mello, and Kleywegt, 2006). Upward forecasting bias is consistent with the RM department using a workaround, or kludge, to address heuristic bias.

We find that the upward forecasting bias, along with demand shock realizations, decreases the fraction of flights subject to pricing on the inelastic side of demand according to internal demand model estimates from 98% to 38%. Interestingly, although routes with nonstop competition feature larger forecasting biases, they retain more frequent inelastic demand.

5 Empirical Model of Air Travel Demand

Our goal is to study the impacts of delegated decision-making and the use of heuristics on market outcomes. While we directly observe how prices are set, we do not directly observe consumer preferences. Moreover, the evidence presented in Section 4 suggests that the internal model of demand may not reflect true underlying preferences that generate demand. Therefore, we estimate an unbiased model of demand. In this section, we present our demand model, estimation procedure, and parameter estimates. We use the model's estimates in counterfactuals.

We maintain a granular market definition, defining a market to be an origin-destination (r), departure date (d), and day before departure (t) tuple. We suppress the r subscript. All parameters are route-specific. 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 $t = T$. In each market t, arriving consumers choose flights from the choice set $J_{t,d}$ that maximize their individual utilities, or select the outside option, $j = 0$. The choice set may change due to a sell out. Our demand model captures all nonstop bookings.

5.1 Utility Specification

Like the firm, we assume that arriving consumers are one of two types, which we label as leisure (L) travelers and business (B) travelers. An individual consumer is denoted by 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 incorporate two assumptions to simplify our analysis. First, we assume that consumers do not choose flights based on remaining capacity, $C_{j,t,d}$. This allows us to avoid modeling infrequent events where a consumer may otherwise choose a less preferred option because there is a higher probability of securing a seat. Second, we incorporate random rationing if demand exceeds remaining capacity.

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

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

where $X_{j,t,d}$ denote product characteristics other than price $p_{j,t,d}$, and preferences are denoted by $(\beta, \alpha_\ell)_{\ell \in \{B,L\}}$. The choice set may vary over time due to sell outs. The term $\xi_{j,t,d}$ denotes an unobserved demand shock that is potentially correlated with price, and $\varepsilon_{i,j,t,d}$ is a random component of utility that is assumed to be distributed according to a type-1 extreme value distribution. Consumer i chooses flight j if and only if $u_{i,j,t,d} \geq u_{i,j',d,t}, \forall j' \in J_{t,d} \cup \{0\}$.

The distributional assumption on the idiosyncratic error term leads to analytical expressions for the individual choice probabilities (Berry, Carnall, and Spiller, 2006). The probability that consumer i chooses flight j is equal to

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

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 can write the market share for flight j as $s_{j,t,d} = \gamma_t s^B_{j,t,d} + (1-\gamma_t)s^L_{j,t,d}$.

5.2 Arrival Processes and Integer-Valued Demand

Whereas the empirical literature commonly assumes market sizes, we model consumer arrivals and estimate arrival rates based on aggregate search counts. This allows us to measure aggregate demand uncertainty. We assume that both consumer types arrive according to time-varying Poisson distributions such that: (i) arrivals are distributed Poisson with rate $\lambda_{t,d}$, (ii) arrivals are independent of price (see Appendix C.4 for supporting evidence) and $\xi_{j,t,d}$; and (iii) consumers solve the above utility maximization problems. With these assumptions, conditional on prices and product characteristics, demand for flight j is equal to

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

Realized demand may be censored, i.e., $q_{j,t,d} = \min\Big\{\tilde{q}_{j,t,d}\,,\, C_{j,t,d}\Big\}$.

5.3 Empirical Specification

The richness of the data allow us capture route- and time-varying demand in a flexible way. All parameters are estimated at the route level. We assume that consumer utility is given by (using the r subscript for this subsection only to stress flexibility)

$$u_{i,j,t,d,r} = \beta_{0,r} - \alpha_{\ell(i),r} p_{j,t,d,r} + \text{FE}_r(\text{Time of Day } j) + \text{FE}_r(\text{Week } d) + \text{FE}_r(\text{DoW } d) + \xi_{j,t,d,r} + \varepsilon_{i,j,t,d,r},$$

where "FE" denotes fixed effects for the variable in parentheses. We parameterize the probability that an arriving consumer is a business traveler as

$$\gamma_{t,r} = \frac{\exp\Big(f_r(t)\Big)}{1 + \exp\Big(f_r(t)\Big)},$$

where $f_r(t)$ is an orthogonal polynomial basis of degree five with respect to days before departure. This specification allows for non-monotonicities while producing values bounded between zero and one. We specify the arrival processes using a multiplicative relationship between day before departure and departure date using fixed effects, i.e., $\lambda_{t,d,r} = \exp(\lambda_{t,r} + \lambda_{d,r})$. We choose this specification because consumer arrivals are observed at the (t,d,r) level of granularity, searches tend to increase over time or evolve discontinuously ($\lambda_{t,r}$), and we observe strong departure-date effects ($\lambda_{d,r}$).

Our method does not require that we observe all searches. Because we observe all bookings, under an additional assumption, and using properties of the Poisson distribution, we can scale up our estimated arrival rates to account for unobserved searches. More precisely, we assign $A_{t,d,r} \sim \text{Poisson}(\lambda_{t,d,r}/\zeta_{t,r})$, where $\zeta_{t,r}$ denotes the fraction of bookings for route r at time t that are made directly with the airline. Implicitly, we assume that the distribution of preferences for consumers that shop via other channels is identical to the observed channel. For example, if observed searches account for 20% of bookings, we can scale up estimated arrival rates by 5× using properties of the Poisson distribution. We conduct several robustness checks to assess the sensitivity of our estimates to our choice in scaling factors (see Section 5.6).

5.4 Estimation Procedure

We estimate demand using a hybrid-Gibbs sampler. This splits up estimation across parameters, as simultaneously drawing from the joint distribution of a large parameter space is computationally challenging. Our approach allows us to estimate hundreds of demand parameters per route, rationalize the large number of zero-sale observations, and maintain a Bayesian IV correlation structure between price and the aggregate demand shock ξ. Our approach builds on the estimation procedure developed by Jiang, Manchanda, and Rossi (2009) by incorporating arrival processes, discrete random coefficients, and censored demand. Hortaçsu, Natan, Parsley, Schwieg, and Williams (2023) conducts Monte Carlo exercises and presents a generalized version of this model that can also accommodate continuous random coefficients.

We present the estimation algorithm below and then describe each step. At each step, we sequentially draw from the marginal posterior distribution groups of parameters, conditional on other parameter draws. We list the prior distribution choices in

Appendix D.2.

Algorithm 1 Hybrid Gibbs Sampler

for $c = 1$ to C **do**
    Update arrivals λ (Metropolis-Hastings)
    Update shares $s(\cdot)$ (Metropolis-Hastings)
    Update price coefficients α (Metropolis-Hastings)
    Update consumer distribution γ (Metropolis-Hastings)
    Update linear parameters β (Gibbs)
    Update pricing equation η (Gibbs)
    Update price endogeneity parameters Σ (Gibbs)
end for

Updating Arrival Parameters We start the sampling procedure by drawing from the posterior distribution of arrival parameters, $\lambda_{t,d} = \exp(\lambda_t + \lambda_d)$. The posterior is derived by defining the joint likelihood of arrivals for each consumer type and quantities sold, conditional on product shares and capacity constraints. The likelihood of arriving consumers is $A_{t,d} \sim \text{Poisson}(\lambda_{t,d}/\zeta_t)$, where ζ is calibrated from the data.

Updating shares. Zero-sale observations are problematic because existing estimation approaches require strictly positive empirical shares, and dropping these observations creates a selections bias in the estimates (Berry, Linton, and Pakes, 2004). Our approach accommodates zeros by treating product shares as unobserved. We use data augmentation to treat shares as latent parameters that we estimate. Conditional on all other parameters, product shares are an invertible function of the demand shocks, ξ. We leverage the stochastic nature of ξ, which we explicitly parameterize. The distribution of unobserved ξ is the source of variation for constructing a conditional likelihood for shares and the pricing equation:

$$\left.\begin{aligned} \xi_{j,t,d} &= f^{-1}\Big(s_{j,t,d} \,|\, \beta, \alpha, \gamma, X\Big) \\ \upsilon_{j,t,d} &= p_{j,t,d} - Z'_{j,t,d}\eta \end{aligned}\right\} \Big| \, t \sim \mathcal{N}_{\text{iid}}(0, \Sigma_t)$$

$$\text{such that} \quad \Sigma_t = \begin{pmatrix} \sigma^2_{t,11} & \rho_t \\ \rho_t & \sigma^2_{t,22} \end{pmatrix},$$

Conditional on the shock υ in the pricing equation, the distribution of ξ, $f_{\xi_{j,t,d}}(\cdot)$, is

$$\xi \Big| \upsilon, \sim \mathcal{N}\left(\frac{\rho_t \upsilon}{\sigma^2_{t,11}}, \sigma^2_{t,22} - \frac{\rho^2_t}{\sigma^2_{t,11}}\right).$$

The density of shares is then given by the transformation $f_{s_{j,t,d}}(x) = f_{\xi_{j,t,d}}\big(f^{-1}(x)\big) \cdot \Big|\mathscr{J}_{\xi_{j,t,d} \to s_{j,t,d}}\Big|^{-1}$, where $\mathscr{J}_{\xi_{j,t,d} \to s_{j,t,d}}$ is the Jacobian matrix of model shares with respect to ξ. To produce the full joint conditional likelihood of shares, we also include the mass function for sales, which is the product of shares and arrivals.

Updating price coefficients, α_B, α_L. We construct the conditional likelihood for $\alpha = (\alpha_B, \alpha_L)$ in a similar manner to the product shares. For any candidate vector of price sensitivity coefficients, we invert the demand system which allows us to derive the likelihood. Conditional on λ, shares, η, β, and Σ, we compute the distribution of ξ and determine the likelihood of a particular draw of α. We impose a log-Normal prior on α, and impose $\alpha_B < \alpha_L$ to avoid label-switching.

Updating the distribution of consumer types, γ. We allow for the mix of consumer types to change over the booking horizon t. We define γ from a sieve estimator of the booking horizon t, and we sample the sieve coefficients, ψ, according to $\gamma_t = \text{Logit}\big(G(t)'\psi\big)$, where $G(t)$ is a vector of Bernstein polynomials. The logistic functional form ensures that the image of γ is in the interval $(0,1)$.

Updating remaining preferences, β. We conduct a Bayesian regression step after adjusting for price endogeneity. Define $\delta_{j,t,d} = X_{j,t,d}\beta + \xi_{j,t,d}$, which is evaluated at

ξ as computed in the previous step. We normalize each component of δ by subtracting the expected value of ξ and dividing by its standard deviation, which enables using a normal conjugate prior.

Updating pricing equation, η. We use a linear pricing equation of the form

$$p_{j,t,d} = Z_{j,t,d}\eta + \upsilon_{j,t,d}.$$

Conditional on shares, λ, γ, α, and β, ξ is known. Therefore, we use the conditional distribution of υ given ξ to perform another Bayesian linear regression in a similar manner to β.

Updating the price endogeneity parameters, Σ. We flexibly model the joint distribution of ξ and υ through Σ_t. We pool observations to estimate the variance-covariance matrix by mapping t to an interval of time. More precisely, we divide the booking horizon into four equally sized 30-day blocks. We use k to denote a block. We draw the variance of this normal distribution with an Inverse-Wishart parameterization. Our prior for Σ_k is $IW(\nu, V)$. We define the vector $Y_k = (\upsilon, \xi)$ to be the collection of residual pairs conditional on block k, and $Y_k \sim \mathcal{N}(0, \Sigma_k)$. The posterior for the covariance matrix Σ_k is given by

$$\Sigma_k \sim IW(\nu + n_k, V + Y_k' Y_k),$$

where block k has n_k observations. This Gibbs step is repeated for each block k, and we sample directly from the conditional posteriors of Σ.

5.5 Identification and Instruments

Estimating models of aggregate demand uncertainty is challenging because it requires separably identifying shocks to arrivals from preferences. Typically arrivals are either assumed or recovered from imposing supply restrictions. We take a different approach by using arrivals data to address this problem. By observing arrivals (and accounting for unobserved arrivals), we can identify preference parameters using the same variation commonly cited in the literature on estimating demand for differentiated products using market-level data. The flight-level characteristic parameters are identified from the variation of flights offered across markets, and we identify the price coefficients using instrumental variables. We construct several instruments and verify that our demand estimates are robust to the choice of instruments.

The first instrument we construct is a cost shifter—we use the opportunity costs calculated by the pricing heuristic. Second, we use AP indicators to account for the fact that prices may adjust even in situations where opportunity costs are not observed to change (see Figure 4). Finally, we consider a network congestion instrument, inspired by "Hausman instruments" or "Fan instruments," that involve cost-related markets. This instrument is defined as the number of inbound (or outbound) bookings to a route's hub airport that can potentially impact the prices consumers face on a given route. Consider a flight from O to D, where D potentially provides service elsewhere. We calculate the number of passengers traveling from D to an alternative destination D'. We assume that demand on leg $D-D'$ is independent of demand on $O-D$. Thus, a positive shock to onward traffic, out of airport D, will create scarcity in both $O \rightarrow D \rightarrow D'$ and $D \rightarrow D'$. This can propagate to prices on $O \rightarrow D$ leg due to the shared capacity constraint, similar in spirit to shared costs across markets with differing demand.[28] RM analysts can capture network scarcity effects by scaling up or down multiple routes' demand predictions via their adjustments, e.g., capturing a demand shock out of a hub when we model demand to the hub.

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

Note that our identification argument does not rely on "optimal pricing." The pricing heuristic's decisions depend on scarcity, and we use its calculated opportunity costs as instruments in a flexible way by also adding quadratic and cubic terms. Our instruments are relevant and highly correlated with price because our pricing equations essentially approximate the heuristic's decisions. For example, suppose that the forecast for a flight is persistently biased upward, but a flight's demand shocks tend to be low. Our approach rationalizes this scenario because large opportunity costs rationalize higher prices. Our estimates recover low ξs which differ in a flexible way from the pricing equation unobservables. These correlations may even be negative; that is, prices may be *high* even though our demand estimates suggest that prices should be *low*. In Appendix D, we report (pseudo) first-stage R^2s for each route, which vary between 60%-90% across routes.

5.6 Demand Estimates

We estimate demand for a large fraction of routes in our sample, however, we do not investigate all routes. We use two selection criteria. First, remove routes with nonstop competition. Therefore, our empirical analysis investigates single-carrier, nonstop routes. Second, we select the first 140 routes, or one-half, of the remaining routes. We do this for computational reasons.

Our estimation sample features lower passenger counts compared to the entire sample, especially as compared to routes with competition. However, the selected routes are not statistically significantly different in terms of the fraction of nonstop and nonconnecting traffic from the single-carrier only routes that we do not investigate. Appendix B.1 presents additional comparisons between the estimation sample and the full sample. In total, we estimate 235,000 demand parameters in our baseline specification.

We summarize our demand results given the large number of parameters estimated. A complete presentation of the demand results appear in Appendix D.1, which pro-

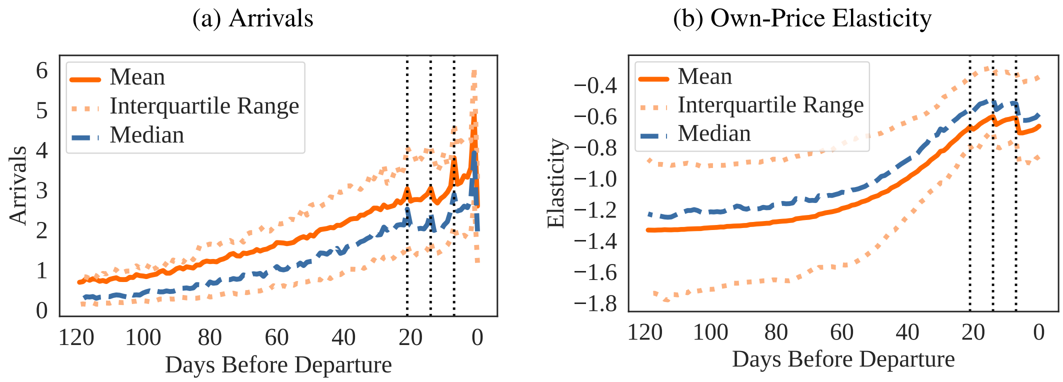
Table 2: Demand Estimates Summary

		Mean	Std. Dev.	Median	25th Pct.	75th Pct.
Parameter						
Leis. Price Sens.	α_L	-1.568	0.769	-1.525	-2.144	-0.931
Bus. Price Sens.	α_B	-0.267	0.213	-0.218	-0.315	-0.122
DoW Prefs	Mon.	–	–	–	–	–
	Tues.	-0.064	0.206	-0.040	-0.194	0.052
	Wed.	-0.026	0.274	-0.012	-0.168	0.112
	Thurs.	-0.032	0.356	-0.014	-0.216	0.116
	Fri.	-0.126	0.331	-0.093	-0.268	0.064
	Sat.	-0.234	0.345	-0.230	-0.430	-0.073
	Sun.	-0.030	0.299	-0.014	-0.182	0.126
Week FE		Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y
Pr(Bus)	γ	0.385	0.191	0.356	0.259	0.462
Summary						
Percent. of 0s		91.401	3.615	92.100	90.100	94.200
Arrivals	A	1.766	1.399	1.171	0.811	2.408
Elasticity	e	-1.079	0.538	-0.970	-1.340	-0.722

Note: Parameter estimates for the 140 routes in the estimation sample. Statistics are calculated over routes, i.e., first the posterior mean of every parameter is calculated for each route. Reported here are aspects of the posterior means across routes.

vides route-level price coefficients, day-of-week preferences, average estimated probability of business, percentage of zero-sale observations, first-stage R^2, average estimated arrivals, empirical and model predicted bookings, and flight-level elasticities. We present these same estimates aggregated over routes in Table 2. We find that leisure consumers are significantly more price sensitive than business consumers. For the average route, 39% of arrivals are business travelers. The interquartile range (IQR) across routes is 26%−46%. Consumers generally prefer Monday travel, and Saturday has the lowest demand. Preferences for Wednesday and Thursday are similar. In our estimation sample, there is consistently a high fraction of zero-sale observations. The average route has 91% zeros, with an IQR of 90%−94%. This is slightly higher (vs. 89%) than the overall sample due to the estimation routes having smaller traffic volume. In general, arrivals are low, at roughly 1.7 searches per day. Finally, we estimate average flight-level elasticities to be near unit elastic, at −1.1, with an IQR of −1.3 to −0.7. Observing near unit-elastic demand does not imply that capacity is not important. In our context, this could stem from the fact that prices are not set by a rational, unitary decision-maker.

Figure 6: Estimated Arrivals and Elasticities, Aggregated across Routes



Note: Arrivals and elasticity statistics calculated over routes.

In Figure 6-(a), we plot arrival rates for the average route as well as the IQR across routes. Although levels of arrivals vary—the interquartile range spans more than a doubling of arrivals—overall, search increases as the departure date approaches. This means that the observed increase in booking rates is not entirely driven by late-arriving, price insensitive consumers. Instead, there is also more interest in travel. In panel (b), we plot the average flight-level price elasticities for the mean, median, and IQR over routes. We find that demand becomes significantly more price inelastic over time. The decline in elasticities close to the departure date does not reflect a decrease in willingness to pay, but rather, very significant price increases (over 70%). We frequently estimate inelastic demand close to the departure date, which we also find using the firm's internal demand model (see Section 4).

Our demand results are robust to a number of alternative specifications, which we report in Appendix D. First, we re-estimate demand for all the routes in our estimation sample using two alternative instrument specifications: solely using the opportunity cost instrument and, separately, solely using the onward connecting traffic instrument. Table 34 and Table 35 present a summary of these alternative demand estimates. Figure 20 graphically compares price coefficients across specifications. We find quantitatively similar preference estimates and demand elasticities. Second, we conduct robustness to the scaling factors used in estimation. We scale arrivals up by an additional 50% and then re-estimate demand for all routes. This allows us to investigate how our demand estimates change with significantly larger arrival rates compared to our baseline estimates. Table 36 contains a summary of the results, and Figure 21 graphically compares price coefficients. We find quantitatively similar estimates: average demand elasticities only change by 0.05. Finally, we estimate demand using a single route ("Route 1"), which has similar demand to the overall average ($\text{elas} = -1.1$), using 14 alternative scaling adjustments. We scale arrivals between 2× and 5× (in increments of 0.5) for all days from departure, and we apply these scaling factors only to days from departure greater than 30, where consumers may primarily search via online travel agencies. We find similar demand elasticities across specifications (see Tables 37-38).

6 Analysis of Department Pricing Input Decisions

6.1 Counterfactual Setup

With demand estimated, we turn to our model of supply. We use the heuristic described in Section 2 to simulate counterfactual market outcomes based on a set of department input decisions.[29] The goal of our first counterfactuals is to evaluate if the observed department inputs are consistent with revenue maximization of the firm. We do not consider alternative incentives or information structures given that we do not observe managerial compensation or variation in organization structure. Prices depend on the fare menu decisions of the pricing department, the demand predictions set by the RM

[29]The psuedo-code for the heuristic, as well as an example, is detailed in Appendix A.

department, and the capacity choice set by the network planning department.

For each counterfactual, we draw initial flight capacities based on the empirical distribution of remaining capacity 120 days before departure. For every route-departure date combination, we simulate flights through departure 10,000 times. We do not endogenize connecting traffic demand. Instead, we handle connecting bookings as exogenous decreases in remaining capacity based on Poisson rates estimated using connecting bookings data. Consumer arrivals and demand come from our model estimates and prices are determined by the heuristic's decisions. Realized demand depends on remaining capacity. If demand exceeds remaining capacity, consumers are offered seats in the random order they arrive. Our counterfactuals allow for within period price dispersion as facilitated by the protection levels set by the heuristic. For example, if a single seat remains at the lowest-available fare and is sold immediately, the next consumer to arrive within a period is offered the next fare with positive inventory remaining.

6.2 Pricing Department Unilateral Deviations

Studying department input decisions is complicated due the richness of managerial decisions. In particular, the pricing department's decisions involve high-dimensional, discrete inputs—we observe roughly 33 million fare decisions. Endogenizing all input decisions is not computationally feasible. We consider a limited set of unilateral deviations.

Our pricing department counterfactual focuses on the coordination problem identified in Section 4. Recall that the pricing department commonly sets fares on the inelastic side of the RM department's demand model. In this counterfactual, we implicitly assume that the pricing department uses the RM department's demand model to remove fares that are on the inelastic side of the demand. The intuition for this counterfactual is that scarcity creates positive opportunity costs. If these opportunity costs are zero, the firm could solve a static revenue maximization problem such that the optimal price makes demand unit elastic. In the presence of scarcity, optimal prices will be higher. Therefore, we retain all fares on the elastic side of the internal demand model. These fares may be offered depending on forecasted and realized demand. We consider this pricing department deviation for every route-departure date-day before departure tuple and aggregate our results.

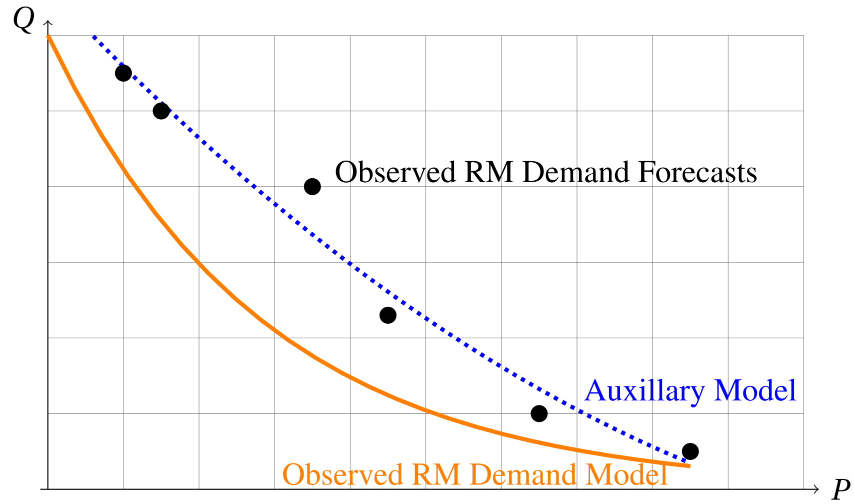
6.3 RM Department Unilateral Deviations

Due to the richness of RM analyst actions, we also consider a limited set of unilateral deviations. To investigate RM decisions, we use an auxiliary model to recover the demand curves consistent with observed analyst adjustments and then manipulate the estimated auxiliary model in counterfactuals. We use techniques from the empirical demand estimation literature to match the forecasting data to our Poisson discrete random coefficients demand model. Figure 7 provides a graphical illustration of the intuition behind our approach. Intuitively, we project the forecasting data onto a flexible model rather than study millions of individual adjustments. Our approach allows us to re-estimate the same 235,000 parameters of our demand model using approximately 70,000 forecasting observations per flight. In total, we use hundreds of millions of forecasting data points. We proceed in two steps.

First, we recalibrate the compound Poisson distributions using a passenger assignment algorithm managed by the RM department. This algorithm classifies all search activity (and purchases) as coming from a "business" or "leisure" traveler. We assume the same total intensity of consumer arrivals and recalibrate the composition of arriving customers ($\gamma_{t,r}$) as

$$\gamma_{t,r}^{\text{forecast}} = \frac{\sum \text{Arrivals}_{t,r}^{B}}{\sum \text{Arrivals}_{t,r}^{B} + \sum \text{Arrivals}_{t,r}^{L}},$$

Figure 7: Auxiliary Model of RM Department Decisions



Note: A graphical representation of modeling RM department decisions. The (solid) orange line depicts an observed demand model. The black dots show (final) flight-level demand predictions after RM analysts make adjustments to the underlying demand model. The (dashed) blue line denotes our auxiliary model which takes the forecasting data and projects it onto a discrete random coefficients demand model.

where $\text{Arrivals}_{t,r}^{B}$ is the total number of arrivals classified as business for route r using the passenger classification algorithm (L is similarly defined). With these estimates, the adjusted arrival processes are $\widehat{\lambda}_{t,d,r}\gamma_{t,r}^{\text{forecast}}$ for business passengers and $\widehat{\lambda}_{t,d,r}(1-\gamma_{t,r}^{\text{forecast}})$ for leisure traffic. We label these Poisson rates $\tilde{\lambda}_{t,d,r}^{B}$ and $\tilde{\lambda}_{t,d,r}^{L}$.

Second, we recover preferences consistent with the RM department's forecasts. The forecasts are quantity demand predictions at the flight, departure date, passenger type, day before departure, and price level. We impose the same demand specification as in our demand model. Because the RM department uses a single-product demand model, we abstract from cross-price elasticities for this analysis and assume arrival rates are equal to $\tilde{\lambda}_{t,d,r}^{\ell}$ for each flight $j \in J_{d,r}$.[30] We match the forecast, $\tilde{Q}_{j,t,d,r}^{\ell}(k)$, at a price k for consumer type ℓ, to the auxiliary model:

$$\tilde{Q}_{j,t,d,r}^{\ell}(k) = \tilde{\lambda}_{t,d,r}^{\ell} s_{j,t,d,r}^{\ell}(k). \tag{1}$$

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

Plugging in a different price, k', results in another matched equation for the same forecast j,t,d,r. Importantly, these forecasts are unconstrained so that predictions are not censored. Taking logs of the Equation 1 and subtracting the log of the outside good share, we use the inversion of Berry (1994) to obtain[31]

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

This provides a linear estimating equation (suppressing subscripts), $\tilde{\delta}=X\tilde{\beta}-\tilde{\alpha}p+u$, where $\tilde{\beta},\tilde{\alpha}^B,\tilde{\alpha}^L$ are preferences to be estimated.[32]

Table 3: Auxiliary Demand Estimates Summary: Forecasting Data

		Mean	Std. Dev.	Median	25th Pct.	75th Pct.
Parameter						
Leis. Price Sens.	α_L	-0.625	0.158	-0.613	-0.729	-0.546
Bus. Price Sens.	α_B	-0.288	0.081	-0.279	-0.345	-0.232
DoW Prefs	Mon.	–	–	–	–	–
	Tues.	-0.089	0.296	-0.072	-0.234	0.105
	Wed.	-0.056	0.384	-0.037	-0.271	0.150
	Thurs.	-0.143	0.412	-0.165	-0.376	0.066
	Fri.	-0.061	0.383	0.001	-0.266	0.182
	Sat.	-0.261	0.435	-0.205	-0.495	0.015
	Sun.	0.005	0.397	0.012	-0.152	0.203
Week FE		Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y
Pr(Bus)	γ	0.211	0.047	0.206	0.176	0.237
Summary						
Elas	e	-0.986	0.196	-0.977	-1.097	-0.872

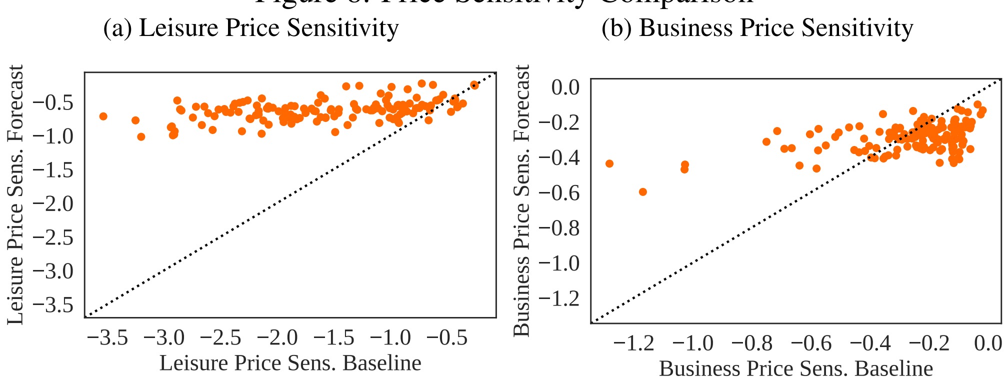
Note: Parameter estimates for the 140 routes in the estimation sample conducted using the forecasting data. Statistics reported are across routes.

[31]This inversion is only possible because the forecasting data are at the consumer-type level. Otherwise, we would have to use the contraction mapping in Berry, Levinsohn, and Pakes (1995) and Berry, Carnall, and Spiller (2006).

[32]This approach results in an estimated "ξ" that also differs across consumer types through u. We set these residuals equal to zero and include our estimated ξ to be consistent with our demand model. We use the mean of the posterior for that observation taken from our demand estimates. This does not greatly impact our findings as the average difference in forecasted demand by replacing the u with ξ is 0.007 (sd = 0.11).

We summarize our results of the auxiliary demand model in Table 3. We find that the forecasting data suggests that leisure travelers are significantly more inelastic than our estimates imply. This is shown in Figure 8, which provides a route-level comparison of price coefficients. Each point is a route. The estimates for the business price sensitivity coefficient (panel b) are more similar, with roughly half the estimates falling below the 45-degree line. Figure 8 shows significant compression of the price coefficients estimated using the forecasting data as compared to the heterogeneity in our model estimates. This is a consequence of the limited heterogeneity incorporated in the RM department's demand model—as discussed in Section 4, each route follows one of six parameter specifications, whereas our model has route-specific parameters. As reported in Table 3, our demand estimates and those derived using the forecasting data are both near unit elastic.

Figure 8: Price Sensitivity Comparison

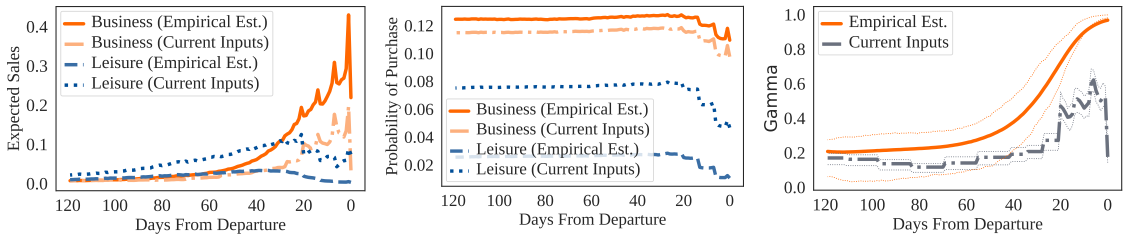


Note: Comparison of the posterior means of the price sensitivity coefficients for each consumer type to the parameter values estimated using the forecasting data. Each observation is a route.

We compare demand predictions using our estimates and those obtained from the auxiliary model in Figure 9. Panel (a) graphs expected demand for both consumer types over time; panel (b) shows consumer-type market shares, and panel (c) shows probability of a traveler being of the business type (γ). While product shares of business travel demand are similar, the forecasting data suggest a larger fraction of demand comes from leisure travelers than our demand estimates suggest.

Figure 9: Comparison of Demand Predictions

(a) Expected Booking Rates (b) Flight-Level Market Shares (c) Probability of Business



Note: Empirical Est. refers to the demand estimates recovered in Section 5. Current Inputs refers to the estimates from the auxiliary model estimated from forecast data. The plots are: (a) flight-level demand over time, (c) flight-level market shares over time, and probability of business over time.

With estimation of the auxiliary model complete, we turn to the set of unilateral deviations that we consider. As discussed in Section 4, the most common analyst adjustment is a scaling of the overall intensity of demand for multiple routes and departure dates simultaneously. This is analogous to adjusting the arrival rates of the model, which motivates how we counterfactually study RM department decisions. We study how RM department decisions affect outcomes by scaling down/up the estimated auxiliary model by χ. The scaled forecasts are then used as an input to the pricing heuristic. We consider $\chi \in \{0.25, 0.5, 0.75, ..., 3.0\}$. A scaling factor less than 1.0 reduces the observed, persistently upward forecasting bias.

6.4 Analysis of Department Input Decisions

We report counterfactual market outcomes for the pricing department unilateral deviation in Table 4, where we normalize outcomes under current inputs to 100 (leisure and business consumer surplus, quantity sold, revenues, and welfare). We find the potentially surprising result that coordinating the fare menus to the RM department's demand model does not increase revenues—in fact, we find that it reduces revenues by 0.9%.[33]

[33] We find that this unilateral deviation results in increased revenues for nine out of 140 routes.

The pricing department unilateral deviation does not increase revenues for a few reasons. First, this counterfactual entails coordinating to a biased input (RM demand model). We find that this counterfactual removes some fares that are on the elastic side of our estimated demand model (see Figure 8-a for a comparison of the price coefficients). We find that this unilateral deviation tends to increase prices early on and results in an 8% decrease in output. Second, the pricing department's decisions interact with a heuristic that is also subject to bias. Removing fares that are on the inelastic side of the internal demand model affects the heuristic in complex ways: a single fare decision can affect future protection levels (and hence, future prices) but the heuristic does not consider these impacts because it is myopic. This highlights the complexity of department decisions, even though the problem has be decomposed. It can be revenue maximizing for the pricing department to include some fares that are on the inelastic side of the demand curve.

Given how fare decisions interact with other inputs and the heuristic, characterizing the optimal pricing menu, even when abstracting from competitive forces, is difficult. While the number of fares the pricing department can choose is limited due to protocols used in the industry (Vinod, 2021), reflecting an environment constraint on the organization (Siggelkow, 2001), it may be revenue maximizing for the firm to use coarse pricing menus as it disciplines how much market segmentation the heuristic believes it will achieve. In addition, adjusting or adding fares has an unclear effect on pricing decisions, because these inputs are then passed to the RM department from which forecasts are built. The pricing department may be acting optimally for the firm given the information it has access to in the spirit of Simon (1956).

Next, we consider RM department unilateral deviations, which we summarize in Table 5. We report market outcomes for reductions in the forecast bias (χ), normalized to the current forecast bias. Our central finding is that unilateral bias reduction reduces revenues and therefore, it is revenue maximizing for the RM department to bias its

Table 4: Pricing Department Deviation Counterfactual

Counterfactual	CS_L	CS_B	Q	Rev	W
Observed Inputs	100.0	100.0	100.0	100.0	100.0
Pricing Department Deviation	77.9	100.4	91.9	99.1	99.0

Note: In counterfactual shown in row (1), we approximate current pricing practices. Counterfactual shown in row (2) examines the pricing department input deviation.

input given the pricing department's choices and the heuristic. Moreover, reducing forecast bias actually increases misallocation by shifting the distribution of sales to earlier arrivals and leaving fewer seats (driven by increased early sell outs) for price insensitive, late-arriving consumers. Leisure consumers benefit from smaller forecasting biases, and business consumers are made worse off.

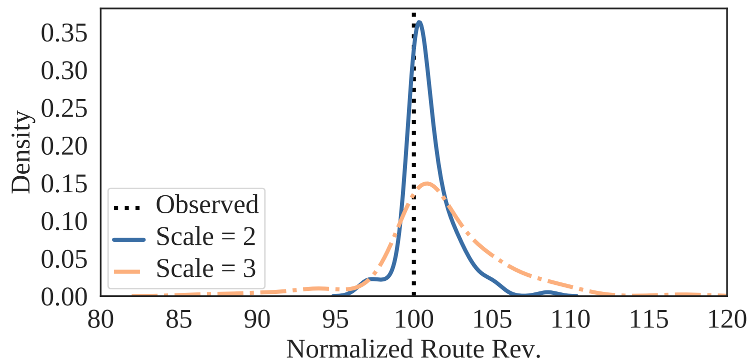
Table 5: RM Department Deviation Counterfactual, Decreasing Bias

Counterfactual	CS_L	CS_B	Q	Rev	W
Scale = 0.25	104.9	98.9	101.1	98.7	98.9
Scale = 0.50	103.4	99.2	100.8	99.1	99.2
Scale = 0.75	101.8	99.6	100.4	99.5	99.6
Observed Inputs	100.0	100.0	100.0	100.0	100.0

Note: In counterfactual shown in row (1), we approximate current pricing practices. Counterfactual shown in row (2) examines the pricing department input deviation.

We also investigate RM department unilateral deviations that exacerbate forecast bias (Figure 10). We find that extreme forecasting biases result in small revenue gains for the firm. For example, overstating demand by 100%, corresponding to the 87th percentile of observed forecasting bias, leads to a 1% increase in firm revenues. Intuitively, if a higher fare results in increased revenues based on our demand estimates, then the forecasting bias may need to be significant in order to ensure that the heuristic does not allocate any inventory to lower fares. We find similar results for all scaling factors between two and three. Under the largest forecasting bias considered (300%, which corresponds to the 97th percentile of observed forecasting bias), we estimate similar revenue gains but also greater dispersion in revenues across route (see Figure 10). Although extreme forecasting bias are observed in the right tail of the forecasting data, we find that RM analysts tend to reduce—and not maintain—these biases over time. In addition to resulting in greater variance in route performance, note that such large biases make forecasts less informative if used outside of the inventory allocation process.

Figure 10: RM Department Deviation Counterfactual, Increasing Bias across Routes



Note: Counterfactual revenues under alternative forecast bias. Scale = 2 implies a forecast bias increase of 100%. Normalized revenue is unweighted.

Our analysis shows that unilateral bias reduction reduces revenues and that observed department decisions are consistent with revenue maximization. This suggests that it may be possible for pricing biases to persist at a sophisticated firm, but the rationalizability of department decisions requires accounting for the fact that a heuristic determines price. Abstracting from the use of heuristics would otherwise suggest that departments are making mistakes if they have the same objective as the firm. However, this does preclude the possibility that market outcomes cannot be "approximated" by abstracting from organizational structure, pricing biases, and the use of heuristics. We consider an alternative model of supply in the next section.

7 Comparison to the Firm as a Unitary Decision-Maker

Our final counterfactual compares market outcomes under observed pricing practices to those that arise by simulating the prices the firm would charge if it were a single entity and maximized revenues accordingly. This allows us to measure if counterfactual welfare is sensitive to abstracting from organizational structure and the use of heuristics.

We simulate prices based on the following dynamic program (DP) (j,d,r subscripts suppressed)

$$V_0(C_0) = \max_{\{p_t\}_{t=0}^{T}} \mathbb{E} \sum_{t=0}^{T} p_t \cdot \min\left\{\tilde{q}_t(p_t),\, C_t\right\},$$

such that $C_{t+1} = C_t - \min\left\{\tilde{q}_t(p_t),\, C_t\right\}$, unsold units are scrapped, and $C_0 \geq 0$ is given. This DP differs from observed pricing in significant ways. First, the DP fully internalizes dynamic opportunity costs, whereas the observed heuristic solves a static problem. Second, the DP also fully considers static opportunity costs, whereas the observed heuristic abstracts from all forms of product substitution. Third, the dynamic program naturally "solves the coordination" problem that we identified where department inputs (and the use of the heuristic) can lead to pricing on the inelastic side of demand. By solving a dynamic program, prices are always on the elastic side of demand (Gallego and Van Ryzin, 1994; Betancourt, Hortaçsu, Öry, and Williams, 2023).

Although DP is well-defined for an arbitrary number of flights, in practice, solving DPs in non-stationary, finite horizon environments is computationally challenging. For example, routes with greater than two flights contain on average 40 billion states. Therefore, we restrict our analysis to routes with at most twice daily service. While we cannot characterize market outcomes under DP for routes with more than two flights a day, larger routes involve the same economic forces.

We make two modeling choices in implementing this counterfactual. First, we use our demand estimates in lieu of the auxiliary forecasting estimates. This mimics standard practices in empirical work of first estimating demand and then counterfactually simulating market outcomes. Second, we retain discrete prices for not only computational reasons, but also to preserve the support of prices consumers typically face. Therefore, we quantify how the distribution of fares decided by the pricing department are affected by assuming prices are chosen according to the DP.

We construct the fare menus as follows. We define the lowest price on the menu to be the fare such that demand is unit elastic on the day before departure with the most price sensitive demand (typically the earliest period). We specify the highest fare on the menu to be the most expensive economy-class fare observed in the data. All observed fares between the mininmum and maximum are retained.

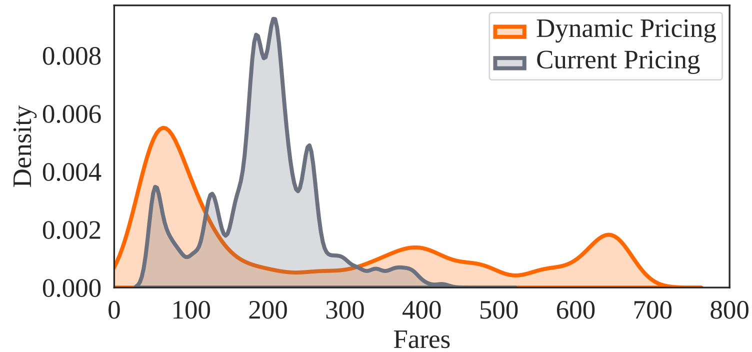
Table 6: Counterfactual Estimates under a Dynamic Pricing Model

Counterfactual	CS_L	CS_B	Q	Rev	W
Observed Inputs	100.0	100.0	100.0	100.0	100.0
Dynamic Pricing Model	107.2	69.2	81.8	114.3	90.8

Note: Comparison of market outcomes under a dynamic pricing model to the current observed pricing practice. The DP results use our demand estimates for optimization. Both results compute surplus using our demand estimates.

In Table 6, we report counterfactual results comparing the DP model to observed practices, which we have normalized to 100 in an analogous way to Table 4. Our key finding is that if the firm were a unitary, rational decision-maker, market outcomes would be significantly different than those observed (see Figure 11 for the distribution of prices offered). Optimal dynamic prices result in increased price targeting that benefits leisure consumer surplus (by 7%) due to lower prices early on. Business consumer surplus is lower (by 31%) due to increased price targeting. The magnitudes are significant. Two additional findings are notable. First, DP results in higher revenues (by 14%) than those observed. Second, if the firm were to adopt DP, we estimate that total welfare would decrease by a significant margin (by 9%).

Figure 11: Comparison of Observed Pricing Practices to DP



Note: Distribution of market prices under observed inputs versus those that arise from assuming that the firm solves a DP.

7.1 Discussion

Our results show that airline pricing is not well approximated by a model that abstracts from organizational structure and use of heuristics. Incorrectly assuming that the firm is a rational unitary decision-maker results in mismeasuring counterfactual welfare. We show the gap between welfare under observed practices and the incorrect model of supply can be significant.

There is a second channel by which not accounting for the fact that prices are set through decomposition and heuristics can affect estimates of welfare and markups. Supply restrictions are often used to estimate demand (e.g., Berry, Levinsohn, and Pakes, 1995). Conlon and Gortmaker (2020) show that these restrictions provide significant identifying power. However, if the correct model of supply involves the use of heuristics and delegated decision-making but a model of the firm as a unitary decision-maker is instead imposed, the resulting demand estimates will be biased.[34] Therefore, our findings are useful for both designing counterfactuals and also for providing guidance on what inferences we draw from observed firm behavior.

[34]We demonstrate that this is also true using our data in Appendix D.5. Intuitively, if we assume prices are set by a rational unitary decision-maker, then demand must be at least unit elastic. However, both our demand estimates and internal demand models from the firm suggest that demand is often inelastic. In order to rationalize observed prices as "optimal," this requires making demand more elastic, decreasing markups (over opportunity costs), and understating consumer surplus.

While we believe that our insights likely apply to many important industries where firms solve complex problems, our results are subject to some important caveats. For example, our analysis abstracts from competitive interactions. However, several of our descriptive results offer useful insights for analyzing these more complex markets. In particular, all routes, regardless of market structure, rely on the same heuristic and single-product demand model. In our context, competitive routes feature more severe pricing biases. A closer approximation of modeling competitive interactions may involve assuming that firms do not internalize all opportunity costs.

Another caveat to our analysis is that we abstract from the additional complexities of studying network planning decisions. Because all department decisions affect the pricing heuristic, we may understate the presence of coordination problems. This may be exacerbated due to revenues being non-monotonic in capacity choice—exemplifying the complexity of individual department decisions, holding other department inputs fixed. While relaxing capacity constraints is always beneficial in the dynamic programs we simulate, because the associated value functions are monotonic in capacity (Gallego and Van Ryzin, 1994; Betancourt, Hortaçsu, Öry, and Williams, 2023), this is not true given the pricing heuristic used by the firm.[35] Complexity is also increased because departments respond to network planning decisions. For example, we observe RM analysts adjust the authorized capacity (willingness to oversell) of flights, which naturally depend on network planning decisions. These adjustments may be optimal for the firm.[36]

[35] In particular, if the lowest fares on the menu are in fact on the inelastic side of demand (as we document in Section 4), then an increase in capacity could cause the heuristic to default to prices that are not revenue maximizing more often, reducing revenues.

[36] Alternatively, these adjustments may reflect incentive conflicts that we do not capture in our analysis. If departments have competing objectives, modeling the organization and what managers do (Gibbons and Henderson, 2012) may be necessary to rationalize observed behavior. How to structure incentives depends on the complexity of the problem (e.g., Bajari and Tadelis, 2001). However, our insight that observed outcomes are inconsistent with a model of the firm as a rational unitary decision maker remain.

8 Conclusion

This paper establishes that relaxing the assumption that firms act as if they are single agents and maximize profits accordingly is critical for understanding how firms set prices. We proceed in three steps. First, we document the extent to which large firms decompose the problem of pricing to distinct departments. Using online job listings and professional networking profiles, we show that cruises, car rentals, ride share companies, hotels, and all major airlines rely on an organizational structure in which departments have distinct pricing-related decision rights. Second, using data and internal models from a large U.S. airline, we establish that pricing is subject to multiple biases that affect all routes, regardless of market structure. Third, using a subsample of single-carrier routes, we show that observed pricing decisions are consistent with departments choosing inputs to maximize revenues around the observed heuristic but diverge from a model where we assume the firm is a single, rational entity. We estimate that if the firm were a unitary decision maker, welfare would decline as a result of increased price targeting, a focus among policy makers given the rise of big data (CEA, 2015).

Our results have important implications for how we model supply. We provide direct evidence using internal models and data that pricing at a sophisticated firm does not fully internalize static and dynamic opportunity costs. An analysis that assumes opportunity costs are fully accounted for when analyzing data or counterfactually simulating market outcomes will obtain biased estimates of markups and welfare if pricing is set through decomposition and heuristics. Imposing alternative supply-side assumptions that capture how firms simplify the complex problems they face may provide better approximations of welfare and market power. This is especially relevant for the study of competitive interactions. Indeed, existing competitive frameworks that assume firms are unitary decision-makers fail to predict observed, post-merger prices (Weinberg and Hosken, 2013). Moreover, recent empirical evidence suggests that more firms are adopting pricing heuristics (Assad, Clark, Ershov, and Xu, 2022; Calder-Wang and Kim, 2023). Accurately accounting for the capabilities and constraints of heuristics and how managers decide their inputs is critical for understanding how efficiently markets operate.

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Appendix

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

by Hortaçsu, Natan, Parsley, Schwieg, and Williams

Table of Contents

A Additional Details on the Pricing Heuristic

The firm optimizes remaining inventory using a heuristic called Expected Marginal Seat Revenue-b or EMSRb (Belobaba, 1987). The heuristic requires three main inputs: a discrete set of fares, demand forecasts for each fare in every period, and a capacity constraint. The heuristic is a generalization of Littlewood's Rule to multiple (> 2) fares. It avoids solving a dynamic pricing problem by considering a sequence of static decisions. The heuristic does not decide a single price, but rather, it allocates the maximum number of seats it is willing to sell at each fare. The lowest-available fare (LAF) is the least expensive fare that receives a positive inventory allocation. If all inventory allocated to this fare sells before re-optimization occurs, the next highest fare with positive allocation becomes the LAF. All flights are reoptimized daily, and all flights, regardless of market structure, are priced using this heuristic.

The key insight and simplification of the heuristic is that it assumes consumers will arrive in increasing order of willingness to pay. It partitions demand along the discrete set of fares and computes protection levels that ensure seats are saved for higher willingness to pay customer segments. For example, if forecasted demand at a high price is high, it may "protect" most remaining capacity for this consumer segment and "reject" forecasted demand at a low price. That is, it will allocate few seats to lower fares and most seats to higher fares.

A.1 Littlewood's Rule

Littlewood (1972) proposed the first inventory allocation rule for the case where there are two consumer segments and two prices. We refer to the two consumer segments as leisure (more elastic) consumers and business (less elastic) consumers. Littlewood's rule assumes that business consumers arrive after leisure consumers. The rule sets a protection level (PL) on the number of seats reserved for business consumers at the higher fare. Simultaneously, it limits the number of seats offered to leisure consumers who are assumed to arrive first. With C seats remaining and a CDF of business consumer arrivals, F_B, Littlewood's rule is

$$p_L = \Big(1 - F_B(\text{PL})\Big)p_B \Longleftrightarrow 1 - F_B(\text{PL}) = \frac{p_L}{p_B},$$
$$\Longrightarrow \text{PL} = F_B^{-1}\left(1 - \frac{p_L}{p_B}\right).$$

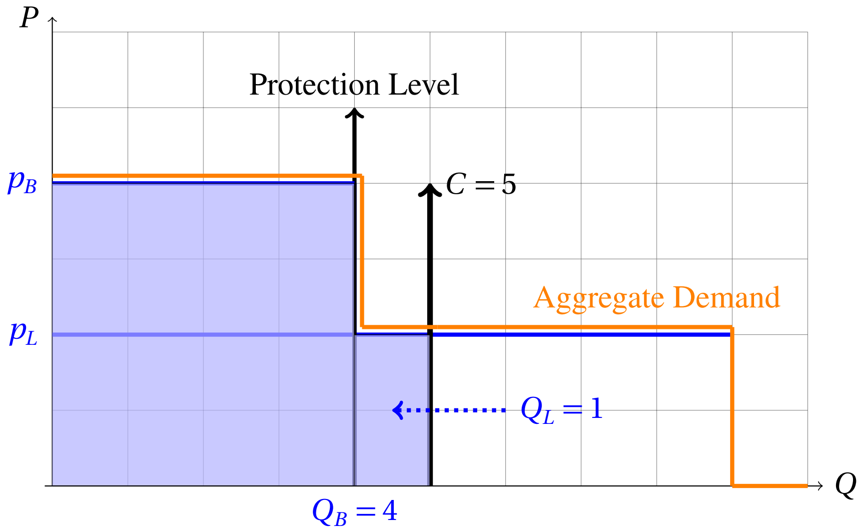
This is equivalent to solving the first-order condition of the associated constrained maximization problem.

Figure 12 illustrates the intuition for how protection levels segment demand without uncertainty. There are two fares, p_L and p_H, and the capacity constraint is five. Given the aggregate demand curve plotted, it is optimal to set the protection level equal to four and only allow one consumer to purchase at p_L. Any other protection level would reduce revenues. For example $\text{PL} = 3$, would allow two purchases at p_L. Setting $\text{PL} = 5$ would cause a seat to go unfilled. When allocating remaining capacity, the firm adds uncertainty into its forecasts. While work in operations commonly uses stochasticity which is not micro-founded e.g., adding normal errors around the demand curve (Belobaba, 1987), we provide a micro-foundation for this uncertainty by using Poisson arrivals.

A.2 EMSRb Algorithm

EMSRb applies the insight of Littlewood's rule to the scenario where there are more than two consumer segments/fare classes. When computing a given fare's protection level, it considers not only the demand at that fare, but also the demand at fares above that level. It calculates an artificial fare called the "super bucket" that is simply the average expected revenue per passenger who are willing to pay that fare or higher (see Figure 13 for an illustration). This is what makes the algorithm a heuristic, i.e.,

Figure 12: Protection Level Intuition



Note: In this protection level illustration, aggregate demand is plotted in orange. With five seats remaining, it is optimal to protect 4 seats for B customers, and only allow one L customer to purchase.

that it differs from an economic model. Once this bucket is formed, Littlewood's rule can be applied because there are now just two fares and two segments. Note that the super bucket represents "business consumers" in Littlewood's rule, as the consumer segments below the current fare have lower willingness to pay. The protection level for that segment is determined, and the process repeats down the demand curve. Critically, the heuristic maintains the assumption that consumers arrive in ascending order of their willingness to pay.

Let K denote the number of fares and assume that fares are sorted such that $p_1 < p_2 < ... < p_K$. Demand for each class k follows distribution F_k. For example, in our empirical model, the demand for each fare class is distributed Poisson with mean $\mu_k(p_k)$. Note that assuming demand is Poisson simplifies this calculation, as the sum of independent Poisson distributions is itself Poisson.

We write the pseudo-code for EMSRb below. The airline runs the heuristic each day before departure (t). In the pseudo-code below, PL are the protection levels. The booking limits BL define the number of seats that can be sold at each fare level. For example, if there are three fares, p_H, p_M, p_L, potential protection levels could be $\mathrm{PL} = (4,3,\cdot)$. There is no protection level for the lowest fare because that segment is provided all remaining seats that are not protected. For example, if $C = 10$, $\mathrm{PL} = (4,3,\cdot)$ implies that $\mathrm{BL} = (10,6,3)$. That is, three seats are allocated to p_L, six allocated to p_M, and the firm is willing to sell all seats at p_H.

Algorithm 2 Psuedo-code for the Firm's Pricing Heuristic used in Counterfactuals

for $k = K, K-1, ..., 2$ **do**

i) Calculate aggregate future demand for fare k, $\mu_k = \sum_{i=t}^{T} q_i(p_k)$,

ii) Calculate partitioned demand, which is the difference in demand between p_k and p_{k+1} where $p_{K+1} = \infty$ as $\mathrm{PD}_k := \mu_k - \mu_{k+1}$, and partitioned revenue for fare k as $\mathrm{PR}_k := p_k \cdot \mathrm{PD}_k$,

iii) Calculate super revenue, $\mathrm{SR}_k := \sum_{b=k}^{K} \mathrm{PR}_b$, and the super bucket, $\mathrm{SB}_k := \mathrm{SR}_k / \mu_k$,

iv) Calculate the fare ratio as $\mathrm{FR}_k := p_{k+1}/\mathrm{SB}_k$, and use Littlewood's Rule to calculate protection level for fare k, $\mathrm{PL}_k := \min\left\{C, {F_{SB}}^{-1}(1-\mathrm{FR}_k)\right\} \in \mathbb{N}$, where $F(\cdot)$ is the distribution of the super bucket,

v) Calculate the booking limit such that $\mathrm{BL}_K = C$ and set

$$\mathrm{BL}_{k+1} := \max\left\{\mathrm{BL}_k - \mathrm{PL}_k, 0\right\} \in \mathbb{N}.$$

end

A.2.1 Fare Class Demand

Aggregate future demand at p_k, μ_k, has a closed form under the assumption of Poisson demand. In our model, $q_{j,t}(p) = \exp(\lambda_t + \lambda_d) s_{j,t}(p)$. Note that in our empirical application, p is a vector of the prices of all flights in the market. Because EMSRb assumes there is a single product, we implement EMSRb under the additional assumption that the firm believes other flights will be priced at their historic average over the departure date and day before departure. We construct residual demand for j, $s_{j,t}(\cdot)$, which enter the heuristic.

Demand at a higher fare class, $k+1$, is equal to $\exp(\lambda_t + \lambda_d)s_{j,t}(p_{k+1})$. Therefore, only $\exp(\lambda_t + \lambda_d)\left[s_{j,t}(p_k) - s_{j,t}(p_{k+1})\right]$ additional consumers are willing to purchase moving from price $k+1$ to k. EMSRb aggregates all future demand by fare class. Because the sum of Poisson distributions is itself Poisson, total partitioned demand for fare-class k at time $t \leq T$ is given by (dropping the j subscript)

$$\mathrm{PD}_k = \sum_{i=t}^{T} \exp(\lambda_i + \lambda_d)\left[s_i(p_k) - s_i(p_{k+1})\right],$$

The super bucket can be calculated as

$$\begin{aligned}\mathrm{SB}_k &= \frac{\sum_{b=k}^{K} p_b \mathrm{PD}_b}{\sum_{i=t}^{T} q_i(p_k)} \\ &= \frac{\sum_{b=k}^{K} p_b \cdot \left(\sum_{i=t}^{T} \exp(\lambda_i + \lambda_d)\left[s_i(p_b) - s_i(p_{b+1})\right]\right)}{\sum_{i=t}^{T} \exp(\lambda_i + \lambda_d) s_i(p_k)}\end{aligned}$$

A.2.2 Example of EMSRb

Consider a single product, sold over $T = 3$ sequential markets, with three fares, $p = \{0.50, 1.50, 3.0\}$, measured in hundreds of dollars. Assume demand is not changing over time and distributed Poisson, i.e., $q_t \sim \text{Poisson}(\lambda \cdot s(p))$, such that $s : \{0.50, 1.50, 3.0\} \longrightarrow \{0.2, 0.1, 0.05\}$, and $\lambda = 10$ each period. Initial capacity is $C = 10$.

Table 7 below shows all objects required to obtain the protection levels and booking limits of EMSRb in the first period. Within the table are superscripts, from a to h. In Table 8, we provide the calculations and mathematical expressions corresponding to those letters.

Table 7: EMSRb Example

Fare	Q	PD	PR	SR	SB	Fare Ratio	PL	BL
3	1.5^{a}	1.5	4.5	4.5	3	0.5	1^{g}	10
1.5	3	1.5^{b}	2.25	6.75^{d}	2.25	0.222^{f}	4	9^{h}
0.5	6	3	1.5^{c}	8.25	1.375^{e}			5

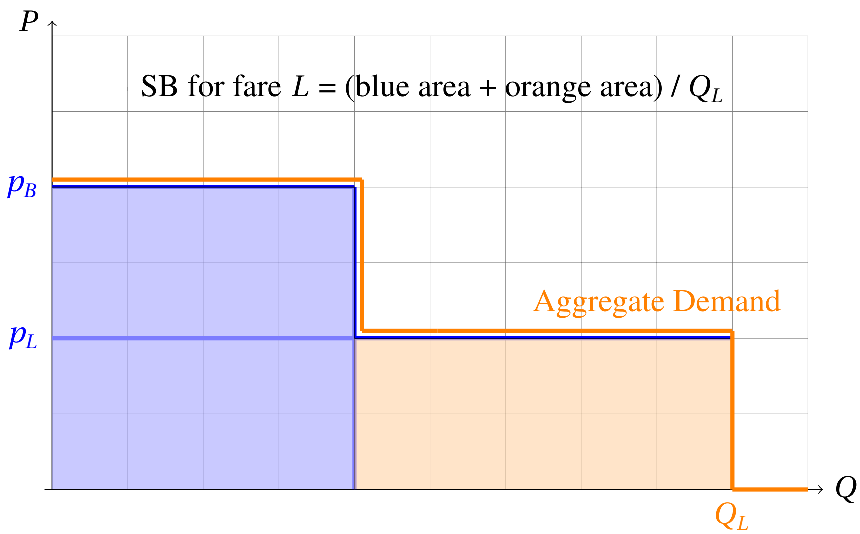
Note: Columns correspond to (in order): fare, partitioned demand, partitioned demand, partitioned revenue, super revenue, super bucket, fare ratio, protection level, and booking limit.

Table 8: EMSRb Example Computations

Letter	Calculation	Expression
a	$0.05 \cdot 10 \cdot 3$	$Q = s(3) \cdot \lambda \cdot T$
b	$3 - 1.5$	$Q(1.5) - Q(3)$
c	$0.5 \cdot 3$	$0.5 \cdot \text{PR}(0.5)$
d	$2.25 + 4.5$	$\text{PR}(1.5) + \text{SR}(3)$
e	$8.25/6$	$\text{SR}(0.5)/Q(0.5)$
f	$0.5/2.25$	$0.5/\text{SB}(1.5)$
g	$\text{InversePoisson}(1 - .5, 1.5)$	$\text{InversePoisson}(1 - \text{Fare Ratio}(3), \text{Q}(3))$
h	$10 - 3$	$C - \text{PL}(3)$

Note: The first column denotes the superscripts marked in Table 7. The second column denotes the calculation required to compute the corresponding letter. Finally, the last column dentes the mathematical expression behind the calculation. Any numbers remaining in the last column denotes the fare.

Figure 13: Super Bucket Calculation Illustration

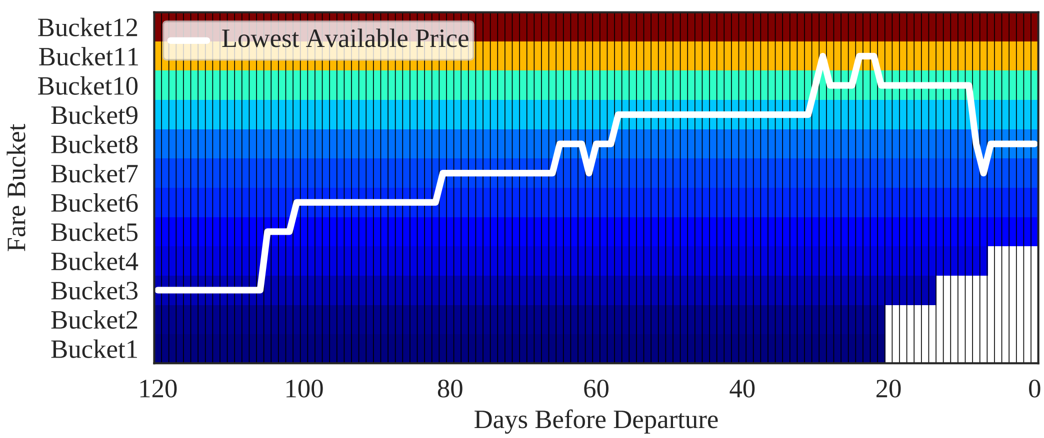


Note: Illustration of the calculation of the super bucket at fare p_L. Note if all consumers had the same willingness to pay, the super bucket would simply be equal to p_L. However, there is an additional segment, willing to pay more than p_L. This is the H segment. The super bucket calculates total revenue above p_L and divides by Q_L.

A.2.3 Empirical Example of EMSRb

We show an example outcome of EMSRb at a point in time in Figure 14. On the vertical axis, we note the discrete set of fares set by the pricing department, with bucket one being the least expensive and bucket twelve being the most expensive. We do not report the actual fare values. There is no variation in the prices for each fare class over time. In the bottom right of the graph, the white space shows that the pricing department has restricted the availability of the lowest fares close to the departure date. That is, there are advance purchase requirements for the lowest fare classes. We do not plot the network planning department's choice of C, nor the demand forecasts themselves. The white line traces out the LAF determined by EMSRb over time. As the graph shows, the LAF is generally increasing over time—prices for the flight increase. The LAF for this particular flight reaches eight unique classes before departure.

Figure 14: 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 bucket; Bucket12 is the most expensive bucket. The color depicts the magnitude of fares—blue are lower fares, red are more expensive. White space denotes no fare availability. The white line depicts the lowest available fare.

B Route Selection and Summary Analysis

We select routes based on the following criteria that we apply to publicly available data:

i) Remove international routes because the DB1B covers solely domestic travel;

ii) Combine nearby airports to "city codes." More specifically, we combine the following airports: (HOU, IAH); (DFW, DAL); (BWI, DCA, IAD); (MDW, ORD); (EWR, JFK, LGA); (LAX, LGB, ONT, SNA, BUR, SBA); (SFO, OAK, SJC);

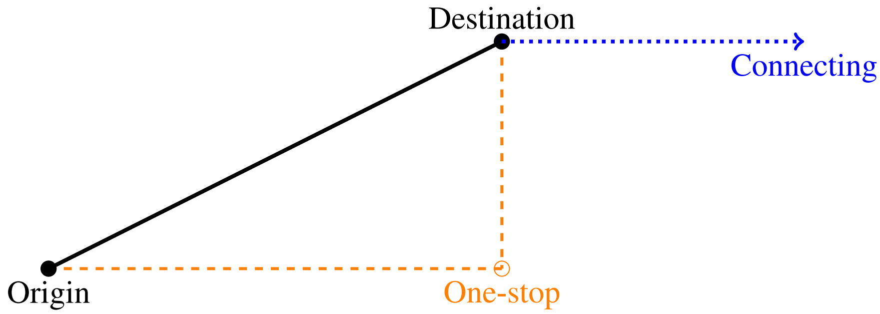
iii) Remove routes where over 10% of passengers fly low-cost carriers (Allegiant, Frontier, Spirit, Southwest, and Sun Country);

iv) Retain routes where at least 25% of passengers fly on our airline;

v) Retain routes where at least 750 passengers fly quarterly;

vi) Remove routes where fewer than 500 passengers fly nonstop.

Figure 15: Nonstop, One-stop and Connecting Traffic



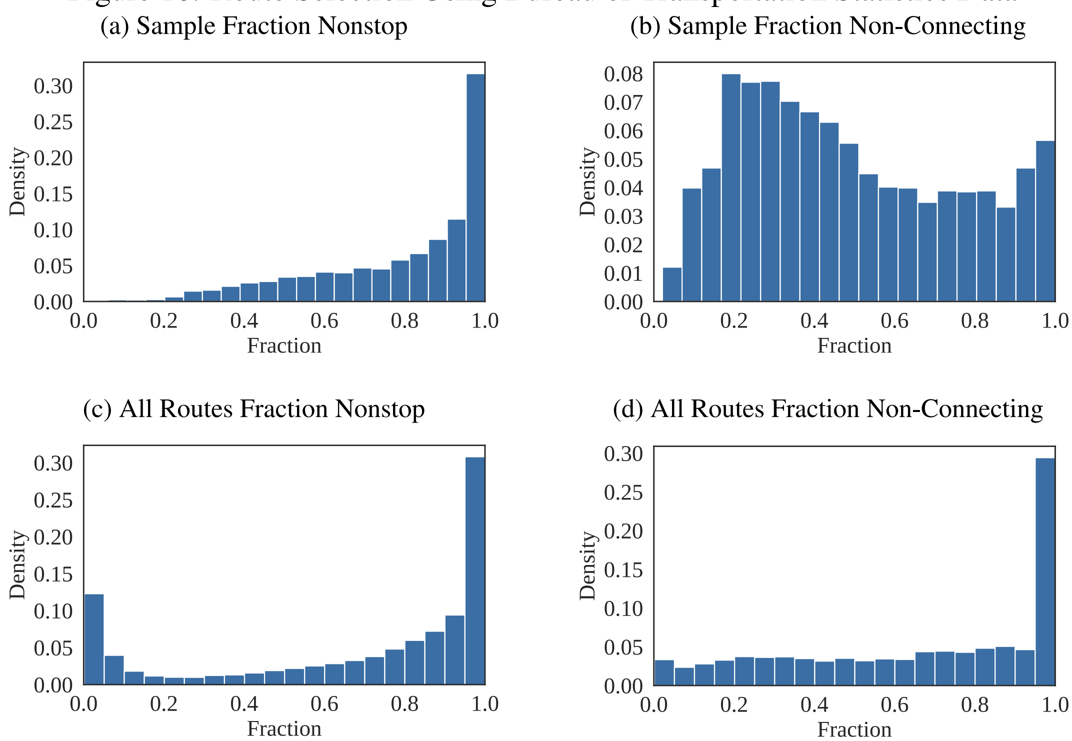
Note: We use the term nonstop to denote the sold black line, or passengers solely traveling between (Origin, Destination). Unless otherwise noted, we will use directional traffic, labeled $O \rightarrow D$. Non-directional traffic is specified as $O \longleftrightarrow D$. The blue, dashed lines represent 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 perform these operations for the first three quarters of the U.S. Department of Transportation's O&D Data Bank (DB1B) separately and take the union of routes.

We then calculate the fraction of route (origin-destination) traffic flying nonstop across quarters. More precisely, we calculate directional traffic flows from a potential origin and destination pair that is served nonstop by our air carrier (see Figure 15). We calculate the fraction of traffic flying from $O \rightarrow D$ nonstop versus flying via a one-stop connection. This compares the solid black line to the dashed orange line. Given the resulting set, we sort routes based on the fraction of passengers flying nonstop (decreasing). We select the first 470 origin-destination pairs from this list.

We also calculate the percentage of traffic that is not connecting. This is the fraction of traffic on the black line in Figure 15 versus the total traffic that includes all potential blue lines. This metric is important because we solely model nonstop demand. We treat connecting traffic as exogenous reductions in remaining capacity.

Figure 16: 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.

Figure 16 presents summary distributions of the two metrics for the routes (ODs) in our sample. 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 competitor flights. In nearly 60% of the markets we study, our air carrier is the only firm providing nonstop service. Our structural analysis will only consider single carrier markets.

B.1 Estimation Sample Comparison

Our estimation sample contains 140 routes. We use two selection criteria. First, we remove routes in our sample that contain nonstop competition. Second, we select the first 140 routes from the resulting set of 280.

Table 9 summarizes traffic flows across the data samples. Compared to all routes in our data set, single-carrier only and our estimation routes tend to be smaller in terms of total number of passengers. Other statistics, including the fraction of traffic traveling nonstop and non-connecting are similar. Figure 17 presents histograms of passenger counts for our entire data sample versus our estimation data sample. In panel (a), we plot origin-destination traffic (the black and orange lines in Figure 15). In panel (b), we plot nonstop traffic (the black line in Figure 15). In panel (c), we plot total traffic (the black and blue lines in Figure 15). In panel (d) we plot the density of fares for our airline, the entire data sample, and the estimation data sample as three separate lines. Finally, in Figure 18, we recreate Figure 16, separating the estimation sample from the entire data sample.

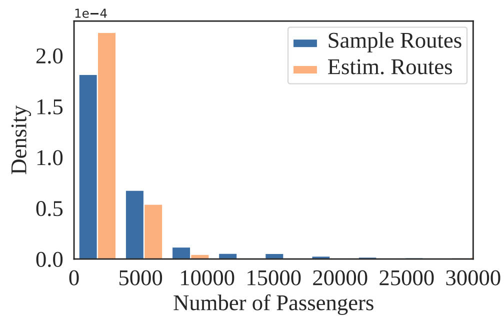
Table 9: Estimation Sample Comparison

Characteristic	All Routes	Single Carrier Only	Estimation
Number of Nonstop Passengers	4415.0	2973.4	2445.2
	(7164.8)	(3018.3)	(2441.4)
Total Number of Passengers	9808.4	8041.2	7014.7
	(10419.0)	(5717.5)	(5023.8)
Number of Local Passengers	4769.4	3281.8	2683.2
	(7357.1)	(3202.4)	(2503.8)
Fraction of Traffic Nonstop	89.3	90.1	89.2
	(15.1)	(15.0)	(16.1)
Fraction of Traffic Non-Connecting	44.7	41.5	40.7
	(23.2)	(22.1)	(20.3)

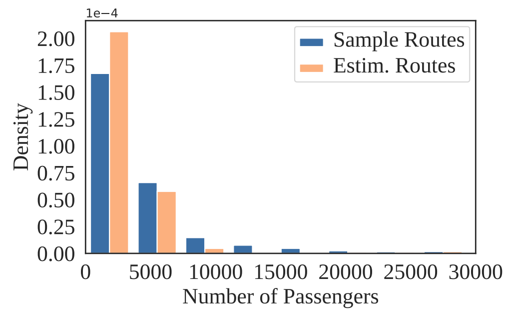
Note: Statistics calculated using the DB1B data for the years 2018-2019. Standard deviations in parenthesis. All routes means all 470 routes in our sample; single carrier only routes are the 279 single-carrier only routes in our sample; estimation routes are the 140 included in estimation.

Figure 17: Sample vs Estimation Sample Route Passenger Count and Fare Comparison

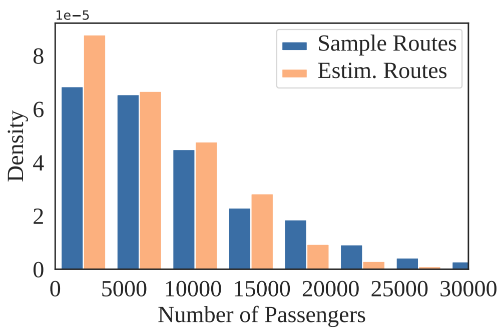
(a) OD Traffic



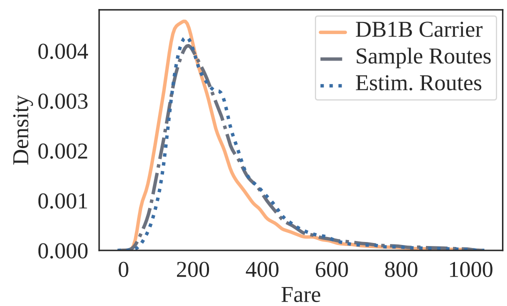
(b) Nonstop OD Traffic



(c) Total Traffic



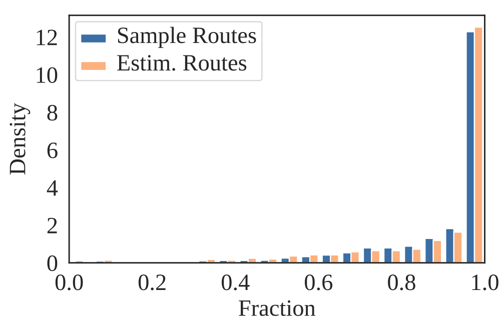
(d) Oneway Fares



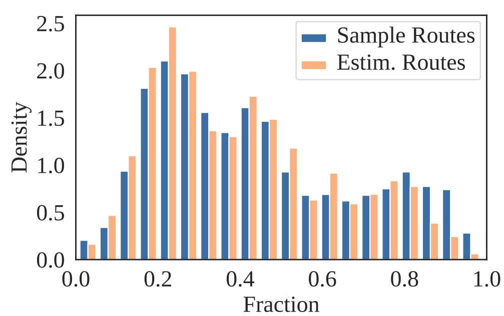
Note: (a) Count of quarterly OD passenger traffic. (b) Count of quarterly OD passenger traffic flying nonstop. (c) Count of quarterly total OD traffic, inclusive of onward connections. (d) Fares per passenger. Sample routes means the 470 routes in our sample; estimation routes means the 140 routes in our estimation sample, and DB1B carrier means all routes served by the airline in the DB1B.

Figure 18: Sample vs Estimation Sample Route Traffic Comparison

(a) Fraction Traffic Nonstop



(b) Fraction Traffic Non-Connecting



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. Blue denotes the entire sample; orange denotes the estimation sample.

C Additional Descriptive Evidence

C.1 Organizational Structure Across Industries

Table 10: Job Descriptions for Pricing Analysts

Company	Industry	Excerpts from Job Description
Alaska Airlines	Airline	"The Senior Pricing Analyst analyzes changes in market conditions such as capacity, competition, schedules, and fares to develop, implement and track appropriate pricing strategies."
American Airlines	Airline	"Working together, the Pricing Analysts focus on competitive analysis to determine optimal pricing across the network and create new fare products to capitalize on changes in consumer buying habits... "
Avis Budget Group	Rental Cars	"Ensure correct application of pricing strategies into applicable systems and databases... Identify and examine markets, geographic regions, competitor pricing, and overall business trends in relation to pricing...Identify and test targeted promotions to align with the organizations pricing strategies"
Azul Brazilian	Airline	"To monitor and help pricing team to react competition pricing changes quickly in order to not lose sales...To define pricing strategies and aid pricing analysts on how to achieve the best performance of their clusters... Responsible for analyz[ing] the markets trends and guide the team to achieve the companyt's goals...."

Continued on next page

Table 10: Job Descriptions for Pricing Analysts (continued)

Carnival Group	Cruises	"Develops strategic cruise pricing for senior management review by analyzing booking trends associated with previous pricing actions...Researches and prepares data on competitor pricing..."
Delta Airlines	Airlines	"Monitor, initiate and communicate industry pricing actions including changes to fare levels, fare rules, policies, and pricing strategy execution... Proactively manage Delta's fare structure including prices and fare rules... Identify and analyze market issues and trends, determining appropriate pricing actions, filing of actions... Synthesize high-level trends and market specific data to establish a fare structure to best segment customers and maximize revenue... Partner with ATPCO, all Global Distribution Systems, the Commercial teams, and other stakeholders to develop, support and enhance the functionality of automated pricing and distribution systems"
Frontier	Airlines	"Develops tactical and strategic pricing initiatives to maximize overall passenger revenue and align with company objectives. Monitors competitive pricing environment and ensures that Frontiers fares are appropriately positioned. Communicates pricing activity to Revenue Management peers and leaders."

Continued on next page

Table 10: Job Descriptions for Pricing Analysts (continued)

Hertz	Rental Cars	"...Provide analysis on pricing trends, market conditions and key performance indicators... Maintain and update pricing for over 250 contracts totaling more than $75 million of annual revenue... Provide detailed pricing analysis and recommendations to align rates with strategies... Produce demand curve analysis and support for pricing decisions...Manage and develop discount reporting across various levels..."
IHG	Hotels	"Collaborate with internal customers i.e. Sales, Legal, Finance/Accounting, Marketing, and Loyalty to design sales agreements and deals to drive revenue."
JetBlue Airlines	Airlines	"As a Pricing Associate Analyst, you will be responsible for ensuring that JetBlue is always competitive in the highly dynamic world of airline pricing by monitoring industry pricing changes filed through a clearinghouse throughout the day and determining and executing JetBlues response. You will also work with the Inventory team to ensure that every market has an optimal pricing structure in place."
MSC Cruises	Cruises	" Manages set-up of Fly & Cruise and Cruise Only, strategic and tactical pricing...Tests and confirm correct functioning and loading of prices onto our booking engines... Performs regular product and price benchmarks for the area of business and has full awareness of what is offered by competitors"

Continued on next page

Table 10: Job Descriptions for Pricing Analysts (continued)

Southwest Airlines	Airlines	"Research competition analysis, follow trends, market share, and competitive landscape to determine current pricing structure. Review competitor sales to determine whether to match pricing. Review price points directed by company marketing efforts. Responsible for specific markets to ensure company competitive landscape benchmarks are met."
Uber	Transportation	"Fares refers to Uber's platform for calculating who pays who what, across all Uber's lines of businesses including mobility products... It processes over 100 billion pricing estimates a year... Fares strives to deliver clear, trustworthy, and intelligent fares for all Uber customers and partners, and consists of... a large platform that works across Pricing, Matching, Maps, Fulfillment, Money, and Support to generate fares for a large number of use cases..."
United Airlines	Airlines	"[Manage] and [optimize] pricing for Uniteds Mexico network, representing $1.1B in annual passenger revenue. [Conduct] strategic analysis for key market overlaps with Low Cost Carriers, and [implement] commercial optimization strategies for Revenue Management and Mexico Sales organization to achieve targeted results."

Continued on next page

Table 10: Job Descriptions for Pricing Analysts (continued)

Universal Orlando Resort	Hotels	"Develop price recommendations for both leisure and group rate programs utilizing elasticity models, trend analysis, and competitive comparisons. Monitor and evaluate effectiveness of current and past rate programs in order to guide pricing decisions. Prepare/update pricing plans and schedules for marketing needs."

Note: Job descriptions excerpted for relevant descriptions of responsibilities for pricing and revenue management analyst positions across firms. Full job listings available at `https://github.com/olivianatan/job_listings`; all listings accessed March 15 and March 16, 2023 except Uber, which was accessed May 4, 2023, and Azul, which was accessed June 4, 2023.

Table 11: Job Descriptions for RM Analysts

Company	Industry	Job Description
Alaska Airlines	Airline	"...responsibilities include analyzing changes in market conditions such as capacity, schedules and fare changes. The Yield Management team will make decisions in the development, implementation, and tracking of appropriate inventory allocation strategies and provide recommendations to generate revenue..."
American Airlines	Airline	"... Yield Management Analysts manage each fare product line by considering passenger demand and optimize inventory for each portion of the network ...'

Continued on next page

Table 11: Job Descriptions for RM Analysts (continued)

Avis Budget Group	Rental Cars	"Managing optimization process, focusing on distribution, pricing, segment management and demand management... Demand forecast management... Supporting the development and maintenance revenue management process and tools..."
Azul Brazilian	Airline	"Parameterizing the portfolio of flights and markets through the PROS system... Analyzing daily sales (macro and micro)... Comparing the future occupancy curve of the flights with the historical one... "
Carnival Group	Cruises	"...providing pricing and inventory recommendations... that helps achieve the highest possible net revenue and occupancy levels... Report on current inventory trends and establishes booking curves ("paces")... Facilitate and audit pricing actions in reservation and internal YODA (Yield Optimization Demand Analytics) systems to ensure support of promotional pieces and deadlines... Monitor competitive products, pricing, and promotional activity... Produce status reports summarizing bookings, revenue, pace, expected and required future progress, current actions, proposed actions...for review at weekly inventory meetings. ...analyze past performance for the same or similar products - booking curves, source of business, achieved yields, and total revenues, etc... Monitor oversells and capacity goals to alleviate buyoffs, buy-downs"

Continued on next page

Table 11: Job Descriptions for RM Analysts (continued)

Delta Airlines	Airlines	"Responsible for flight level revenue optimization by properly valuing our passengers and forecasting future demand levels... Monitor and update the flight level demand forecasts through the analysis of historical and future booking trends, the pricing environment, industry capacity trends, the competitive landscape, and other factors... Establish and maintain the flight level overbooking forecasts through the analysis of no-show behavior trends... Evaluate performance and post-departure trends to identify and leverage future opportunities while maximizing the revenue potential for each market..."
Frontier	Airlines	"Monitors and establishes inventory levels based on revenue data of passenger loads, capacity, group bookings, and demand in order to maximize revenues through the use of forecasting tools... Maximizes revenues through seat allocation... Optimizes and validates forecasted demand of select markets.. Analyzes market influences, evaluates market historical performance and identifies market demand patterns... Recommend market/flight-level forecast strategies... Monitors PROS/DAXPY systems to make sure they are current with upgrades/technical issues... Audits effective usage in PROS of all influences, forecast accuracy and demand shifts"

Continued on next page

Table 11: Job Descriptions for RM Analysts (continued)

Hertz	Rental Cars	"The Revenue Management Analyst is responsible for managing car rental pricing and availability for Hertz Global Holdings... Implement mix optimization plan along key segmentation factors; including product, channel, and customer segments; to support Revenue Per Day (RPD), Revenue Per Vehicle/Unit (RPV/U), and market share improvement targets. Identify and examine market, geographic regions, competitor landscape, and overall business trends in relation to revenue management."
IHG	Hotels	"...Implement and support Hotel pricing, market strategy, yield, distribution & selling strategies, and revenue management best practices. Manage hotel revenue generation & maximization through full utilization of hotel systems, business processes, and specifications... Prepare a monthly, rolling 3 months, and full-year forecast for rooms... Conduct weekly rate/sell strategy (yield) meetings...Drive upselling program for rooms and Non-room inventory with the target... Monitor and determine demand periods for function space, rooms, and catering through an analysis of historical data and current bookings... Responsible for tracking and analyzing booking pace, group wash, cut-off enforcement for groups, and denied and regretted business..."

Continued on next page

Table 11: Job Descriptions for RM Analysts (continued)

JetBlue Airlines	Airlines	‘...responsible for the revenue performance for a portfolio of JetBlue routes, often representing more than $100 million of revenue under direct control... use inventory controls to determine the optimal fare to sell at any given moment in time to maximize each flights revenue.”
MSC Cruises	Cruises	“...Assist with budgeting/forecasting by pulling historical and recent data and creating models for passenger volume and revenue targets... Perform weekly competitive benchmarking to monitor major cruise lines’ pricing compared to that of MSC’s and flag where highly overpriced or underpriced... Make price change recommendations based on trends...”
Southwest Airlines	Airlines	“Responsible for ensuring daily air revenue generation meets or exceeds Company goals while maintaining our low cost brand. Ensure the Revenue Management System has the most accurate inputs and is calibrated accordingly. Recommend and support execution of full-scale strategic changes based on statistical analysis and simulation modeling...”

Continued on next page

Table 11: Job Descriptions for RM Analysts (continued)

Uber	Transportation	"Control the dynamics of all of Uber's markets... We focus on areas like dynamic pricing (surge pricing, upfront pricing), intelligent dispatching (matching algorithms, dispatch paradigms), and supply positioning... The goal of these systems is to dramatically lower cost & ETAs for riders, increase revenue for driver partners, improve the overall efficiency and utilization of Uber's fleet of supply..."
United Airlines	Airlines	"Forecasts customer demand and sets overbooking levels...Analyze trends in bookings, revenue and market dynamics..Assess demand patterns and competitive landscape...Segment customers based on market conditions...Develop fare structure/demand forecast to optimize revenue..."
Universal Orlando Resort	Hotels	"...Analyze revenue management system output for forecast and optimization anomalies through the use of statistical and mathematical optimization models...Prepare/update forecast and business plans and forecasting models...Prepare and analyze data relating to booking trends, demographics, stay patterns, booking source, ROI/Incrementality analysis, and other market data..."

Note: Job descriptions excerpted for relevant descriptions of responsibilities for revenue management analyst positions across firms. Full job listings available at `https://github.com/olivianatan/job_listings`; all listings accessed March 15 and March 16, 2023 except Uber, which was accessed May 4, 2023, and Azul, which was accessed June 4, 2023.

C.2 Synthesized Data Examples

Table 12: Synthesized Booking Data Example

Variable	Value
Origin	ABC
Destination	DEF
Routing	ABC DEF
Flight Number	1234
Reservation Number	GH1234
Departure Date	2018-08-18
Departure Time	08:00:00
Arrival Time	18:00:00
Currency	USD
Total Fare Paid	400
Number of Pax. Booked	2
Fare Per Passenger	200
Passenger Type	Leisure
Distribution Channel	Direct

Note: Variables show columns included in the actual data; values are synthesized.

Table 13: Synthesized Inventory Data Example

Variable	Value
Origin	ABC
Destination	DEF
Flight Number	1234
Departure Date	2018-08-18
Departure Time	8:00:00
Arrival Time	10:30:00
Booking Date	2017-10-01
Bucket 1 Allocation	95
Bucket 1 Fare	$1000
Bucket 2 Allocation	90
Bucket 2 Fare	$800
⋮	
Bucket N Allocation	3
Bucket N Fare	$200
Opportunity Cost	175
Actual Capacity	100
Authorized Capacity	100
Total Bookings Made	5
Space Available	95.0
Lowest Available Fare	200
Lowest Available Class	N
Flight Forecast	109.8

Note: Variables show columns included in the actual data; values are synthesized.

Table 14: Synthesized Search Data Example

Variable	Value
Cookie ID Number	123456789
Visit ID Number	1
Hashed Consumer ID	987654321
Time on Website	00h:02m:34s
Number of Clicks	10
Click Number	8
Session Quality Score	99
Referrer	N/A
Screen Size	1280 x 800
Operating System	Windows 11
Browser Version	Firefox
Search Date	2017-10-01
Origin	ABC
Destination	DEF
Departure Date	2018-08-18
Return Date	—
Ticket Type	Revenue
Passenger Type	Leisure
Lowest Available Fare	200
Number of Passengers	2
Route	ABC DEF

Note: Variables show columns included in the actual data; values are synthesized.

Table 15: Synthesized Forecasting Data Example

Variable	Value
Origin	ABC
Destination	DEF
Date	2017-10-01
Flight Number	1234
Departure Time	8:00:00
Arrival Time	10:30:00
Departure Date	2018-08-18
Equipment	DC-3
Cabin	Economy
Booking Class	N
Lowest Available Class	N
Passenger Type	Leisure
Forecasting Date	2017-10-01
Base Class Forecast	0.33236
Adjusted Class Forecast	0.31236

Note: Variables show columns included in the actual data; values are synthesized.

Table 16: Example Fare Listing for International Airline

Fare	Airline	Fare Class	Fare Type	Fare ($)	Cabin	AP Require.
GS5XBALG	Air France	G	One-Way	35	Economy	40
XS5GBALG	Air France	X	One-Way	42	Economy	35
VS59BALG	Air France	V	One-Way	53	Economy	30
RS59BALG	Air France	R	One-Way	67	Economy	30
NS58BALG	Air France	N	One-Way	83	Economy	25
GS5XBBST	Air France	G	One-Way	85	Economy	40
XS5GBBST	Air France	X	One-Way	92	Economy	35
TS50BALG	Air France	T	One-Way	93	Economy	
VS59BBST	Air France	V	One-Way	102	Economy	30
ES57BALG	Air France	E	One-Way	106	Economy	20
LS50BALG	Air France	L	One-Way	109	Economy	
RS59BBST	Air France	R	One-Way	116	Economy	30
QS57BALG	Air France	Q	One-Way	128	Economy	20
HS50BALG	Air France	H	One-Way	129	Economy	
NS58BBST	Air France	N	One-Way	132	Economy	25
TS50BBST	Air France	T	One-Way	143	Economy	
OS59BBNB	Air France	O	One-Way	146	Economy	30
ES57BBST	Air France	E	One-Way	155	Economy	20
AS56BALG	Air France	A	One-Way	158	Economy	15
LS50BBST	Air France	L	One-Way	158	Economy	
KS50BALG	Air France	K	One-Way	159	Economy	
GS5XBEFX	Air France	G	One-Way	174	Economy	40
QS57BBST	Air France	Q	One-Way	178	Economy	20
HS50BBST	Air France	H	One-Way	179	Economy	
XS5GBEFX	Air France	X	One-Way	180	Economy	35
VS59BEFX	Air France	V	One-Way	192	Economy	30
SS55BALG	Air France	S	One-Way	194	Economy	10
FS50BALG	Air France	F	One-Way	202	Economy	
RS59BEFX	Air France	R	One-Way	205	Economy	30
AS56BBST	Air France	A	One-Way	208	Economy	15
KS50BBST	Air France	K	One-Way	209	Economy	
ZS59BBNB	Air France	Z	One-Way	215	Economy	30

Note: Active fares for Air France, London Heathrow (LHR) to Paris Charles de Gaulle Airport (CDG) for Sep 1, 2023. Fares obtained Jun 9, 2023. Data obtained from ExpertFlyer.com.

C.3 Search Data Cleaning and Clickstream Patterns

The clickstream data are constructed from consumer activity on the airline's website and mobile sites. Both consumer-level and interactions-level data are collected. Consumer-level data includes browser and device information. This information can be used for bot detection, as we describe below. We use cookie information to identify users using a hashed cookie identifier, which allows us to track users across enumerated sessions unless an individual clears their current browser's cache, switches devices, uses incognito mode, or switches browsers. If a user logs into their loyalty account, we are able to match their behavior across different cookie identifiers using their hashed airline loyalty identifier. By interactions data, we mean a set of "clicks" that are tracked, including users arriving to the website, logging into the website, searching for flights, making a purchase, etc. For this project, we only use clicks related to login, flight search, and viewing search results pages.

We use the following cleaning criteria on the raw data:

i) We remove observations in which the departure, arrival, or return dates are mismeasured. These values contain "N/A" in the relevant fields;

ii) We keep activity related to one-way or round-trip travel;

iii) We exclude observations in which the number of connections is greater than two;

iv) We remove activity related to refunds or flight changes;

v) We exclude sessions that are flagged as bot or automated traffic using a session quality measure included in the clickstream data. The quality score ranges from one to 100 and is provided by the web analytics service. We remove observations in which the score equals one, which is assigned to internet activity that is consistent with bot traffic.

We verify that our cleaning script generally removes observations where multiple of the following hold: (a) activity originates from other countries, (b) activity originates from a Linux operating system, (c) user computers do not indicate a monitor is being used (i.e., there is no screen resolution), and (4) activity has total time on the site measured to be in the milliseconds.

We create three data tables based on processed clickstream data. The first we call "logins." These entries are recorded when a consumer logs into her loyalty account. Each login contains a hashed cookie identifier and device identifier. By processing all logins, we create a map of hashed consumer ids to hashed cookie ids. We use this mapping to investigate reshopping (shopping for the same trip over multiple search dates) behavior.

The second data set we construct are "impressions." These entries correspond to the information consumers see when viewing flight result pages. For this project, we use these data to augment our market size calculations that we describe below. Our cleaned impressions sample contains 143 million observations that we use to construct arrivals.

The third data set we construct are "searches." These entries are recorded when a consumer submits a search query on the airline's website. Table 14 contains a synthesized search query example. Note that the impressions data also contain these key variables, but they also include flight-specific information for each flight the consumer observes. We do not use the impression results in this project. Our cleaned search query sample contains 68 million observations that we use to construct arrivals.

Arrivals are calculated at the route, departure date, search date level. We first check for duplicate entries at the cookie-origin-destination-departure date-return date level in both the impressions and search data. For example, if a consumer searches an itinerary, adjusts the departure date, and then searches the original itinerary again, we record two entries of search activity instead of three. With these cleaned data, we sum the following counts:

i) Count of the total number of passengers across all unique search queries for one-way and round-trip searches where the route is the outbound leg,

ii) Count of the total number of passengers across all unique search queries where the route is the return of a round-trip itinerary,

iii) Count of the total number of passengers across all unique impressions for one-way and round-trip searches where the route is the outbound leg,

iv) Count of the total number of passengers across all unique impressions where the route is the return of a round-trip itinerary.

We calculate and add (iii) and (iv) to our measure of arrivals since some consumers are redirected to the firm's website from an internal source where the search query is not recorded. In calculating arrivals, we first verify if recorded impressions do not have corresponding searches to ensure no double-counting.

C.4 Booking Trends Around Advance Purchase Cutoff Times

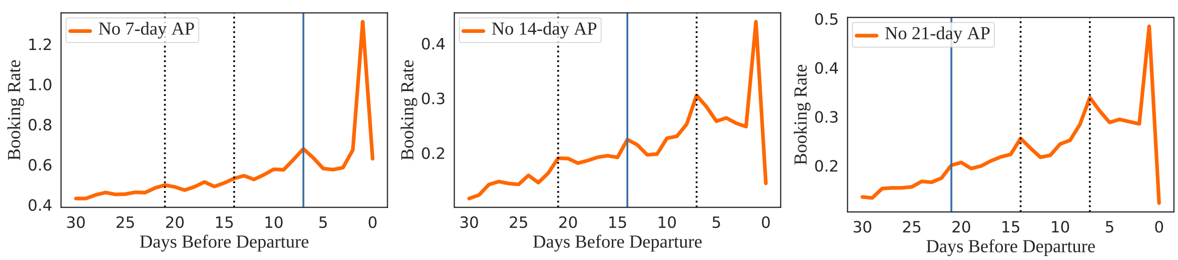
There are small spikes in the booking rates across all channels when AP fares expire. This includes 7, 14, and 21 days before departure. Although this may suggest some consumers strategically time market participation, we also find support for the assumption that these days simply have higher demands. This may be due to travel websites that suggest consumers should purchase before a certain time.

We create three subsets of the data based on the absence of AP requirements. For example, there are routes in our data that never have 7-day AP fare requirements for the entire sample period. We repeat this process for routes that never have 14-day AP requirements and routes that never have 21-day AP requirements. In Figure 19, we plot the average booking rates over days before departure for these three subsets of the data.

We focus on the last 30 days before departure. The plots show that there is bunching at 7, 14, and 21 days before departure, respectively, even though these routes do not have such requirements (and thus no systematic corresponding price increases). That is, booking rates are higher, even though there is no discontinuity in fares after crossing 7, 14, and 21 days before departure, respectively. We use this evidence to motivate including time-varying fixed effects in our arrival processes. We do not model arrivals as being a function of price. Rather, we maintain the commonly used assumption that consumer choice is a function of price, conditional on arival.

Figure 19: Booking Rates for Routes without AP Discounts

(a) No 7-Day AP (b) no 14-Day AP (c) no 21-Day AP



(a) Average booking rate for routes without a 7-day AP discount. (b) Average booking rate for routes without a 14-day AP discount. (c) Average booking rate for routes without a 21-day AP discount.

D Additional Demand Tables

D.1 Route-Level Demand Estimates

The following tables provide route-level demand estimates for the 140 routes included in our structural analysis.

Table 17: Demand Results Summary Table

Route		1	2	3	4	5	6	7	8	9	10
Parameter											
Leis. Price Sens.	α_L	-1.038	-2.163	-0.430	-0.533	-2.135	-2.373	-3.201	-1.072	-2.466	-1.874
		(0.068)	(0.071)	(0.037)	(0.047)	(0.150)	(0.095)	(0.130)	(0.047)	(0.059)	(0.061)
Bus. Price Sens.	α_B	-0.247	-0.418	-0.036	-0.104	-0.088	-0.218	-1.283	-0.067	-0.471	-0.304
		(0.036)	(0.064)	(0.010)	(0.018)	(0.015)	(0.025)	(0.132)	(0.014)	(0.029)	(0.040)
DoW Prefs	Mon.	0.049	0.012	-0.193	-0.527	0.092	–	–	0.267	0.383	0.496
		(0.053)	(0.066)	(0.054)	(0.087)	(0.069)	–	–	(0.081)	(0.091)	(0.148)
	Tues.	0.009	0.219	0.202	-0.431	-0.131	-0.083	-0.039	0.048	0.382	0.333
		(0.054)	(0.069)	(0.058)	(0.092)	(0.062)	(0.069)	(0.085)	(0.113)	(0.087)	(0.123)
	Wed.	0.163	0.189	0.290	-0.124	-0.102	-0.012	-0.087	–	0.307	0.577
		(0.054)	(0.073)	(0.055)	(0.095)	(0.066)	(0.066)	(0.085)	–	(0.077)	(0.133)
	Thurs.	0.137	0.110	0.319	-0.046	-0.160	0.001	-0.124	-0.147	0.342	0.228
		(0.051)	(0.060)	(0.055)	(0.089)	(0.074)	(0.070)	(0.078)	(0.081)	(0.076)	(0.116)
	Fri.	0.148	0.103	0.184	–	–	-0.094	-0.261	0.030	0.220	0.133
		(0.050)	(0.065)	(0.049)	–	–	(0.069)	(0.080)	(0.091)	(0.073)	(0.115)
	Sat.	–	-0.064	-0.041	-0.049	-0.157	-0.095	-0.030	-0.238	-0.199	–
		–	(0.055)	(0.052)	(0.092)	(0.070)	(0.063)	(0.080)	(0.087)	(0.066)	–
	Sun.	0.065	–	–	-0.189	-0.024	0.231	-0.007	0.028	–	0.130
		(0.051)	–	–	(0.087)	(0.066)	(0.072)	(0.092)	(0.081)	–	(0.128)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.217	0.574	0.265	0.134	0.704	0.780	0.187	0.275	0.458	0.305
Summary											
Percent. of 0s		85.3	94.5	88.2	85.7	94.0	92.0	95.4	92.5	94.8	95.7
First stage R^2		0.828	0.690	0.614	0.730	0.820	0.771	0.868	0.777	0.655	0.587
Arrivals	A	2.471	1.019	1.894	3.572	3.914	2.920	0.617	0.703	0.890	0.358
Emp. Q	Q	0.279	0.226	0.228	0.249	0.195	0.172	0.095	0.192	0.243	0.104
		(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)
Model Q	$E[Q]$	0.281	0.229	0.229	0.252	0.210	0.179	0.096	0.188	0.244	0.102
		(0.03,1.02)	(0.02,0.78)	(0.04,0.70)	(0.07,0.77)	(0.04,0.64)	(0.03,0.55)	(0.01,0.40)	(0.02,0.67)	(0.02,0.88)	(0.01,0.34)
Elas	e	-1.241	-0.872	-0.822	-1.775	-0.298	-0.664	-1.747	-1.083	-1.148	-1.497
		(-2.07,-0.53)	(-1.05,-0.63)	(-1.35,-0.24)	(-2.69,-0.70)	(-0.47,-0.21)	(-1.00,-0.52)	(-2.09,-0.85)	(-1.79,-0.14)	(-1.44,-0.71)	(-2.15,-0.57)
Number of Flights		488	1,290	509	107	331	315	670	752	1,060	487
Number of Dep. Dates		393	379	393	107	163	203	392	387	274	238
Number of Obs.		58,076	156,777	60,721	12,791	38,847	37,319	79,955	89,486	124,843	56,307

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 18: Demand Results Summary Table

Route		11	12	13	14	15	16	17	18	19	20
Parameter											
Leis. Price Sens.	α_L	-3.536	-0.567	-0.767	-0.403	-1.928	-1.455	-2.075	-2.906	-2.518	-0.929
		(0.196)	(0.102)	(0.108)	(0.039)	(0.105)	(0.086)	(0.142)	(0.301)	(0.082)	(0.076)
Bus. Price Sens.	α_B	-0.229	-0.317	-0.192	-0.097	-0.334	-0.299	-0.122	-0.715	-0.197	-0.114
		(0.022)	(0.067)	(0.040)	(0.016)	(0.049)	(0.033)	(0.021)	(0.178)	(0.020)	(0.021)
DoW Prefs	Mon.	0.132	0.381	0.103	0.169	–	–	–	0.281	0.207	–
		(0.049)	(0.100)	(0.120)	(0.057)	–	–	–	(0.082)	(0.033)	–
	Tues.	0.289	-0.096	0.030	-0.050	-0.239	0.042	-0.052	0.238	0.174	-0.131
		(0.068)	(0.073)	(0.129)	(0.059)	(0.100)	(0.073)	(0.066)	(0.091)	(0.037)	(0.080)
	Wed.	0.138	0.056	-0.025	-0.054	-0.364	-0.011	-0.197	0.128	0.113	-0.168
		(0.053)	(0.074)	(0.124)	(0.060)	(0.093)	(0.080)	(0.069)	(0.076)	(0.038)	(0.075)
	Thurs.	0.048	–	-0.146	-0.020	-0.325	-0.012	-0.252	–	–	-0.241
		(0.060)	–	(0.123)	(0.059)	(0.091)	(0.066)	(0.063)	–	–	(0.075)
	Fri.	–	0.023	–	–	-0.365	-0.050	-0.380	-0.088	-0.172	-0.381
		–	(0.074)	–	–	(0.082)	(0.075)	(0.064)	(0.070)	(0.036)	(0.076)
	Sat.	-0.168	0.389	-0.112	-0.240	-0.238	-0.429	-0.372	-0.068	-0.160	-0.338
		(0.053)	(0.111)	(0.109)	(0.056)	(0.097)	(0.088)	(0.074)	(0.087)	(0.038)	(0.076)
	Sun.	-0.051	0.875	0.015	0.144	-0.452	-0.295	-0.323	0.490	-0.272	-0.278
		(0.059)	(0.155)	(0.106)	(0.059)	(0.080)	(0.060)	(0.077)	(0.106)	(0.035)	(0.076)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.547	0.203	0.215	0.255	0.349	0.274	0.505	0.207	0.441	0.476
Summary											
Percent. of 0s		90.9	84.5	94.3	88.4	90.7	91.8	90.1	93.0	87.0	91.2
First stage R^2		0.849	0.760	0.798	0.649	0.798	0.653	0.617	0.611	0.827	0.601
Arrivals	A	1.818	3.020	2.463	2.185	0.849	0.893	1.113	1.005	5.725	0.983
Emp. Q	Q	0.571	0.288	0.099	0.225	0.128	0.302	0.249	0.097	1.195	0.118
		(0.00,3.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,6.00)	(0.00,1.00)
Model Q	$E[Q]$	0.569	0.288	0.106	0.226	0.127	0.297	0.247	0.097	1.199	0.118
		(0.04,2.13)	(0.08,0.98)	(0.02,0.28)	(0.04,0.72)	(0.01,0.46)	(0.02,1.05)	(0.02,0.86)	(0.01,0.35)	(0.11,4.26)	(0.02,0.34)
Elas	e	-0.479	-1.565	-1.499	-0.723	-1.188	-1.667	-0.571	-1.474	-0.631	-0.609
		(-0.70,-0.24)	(-2.75,-0.73)	(-2.27,-0.80)	(-1.30,-0.30)	(-1.91,-0.40)	(-2.58,-0.55)	(-0.83,-0.18)	(-2.32,-0.62)	(-0.87,-0.35)	(-1.12,-0.19)
Number of Flights		1,453	217	123	444	304	960	647	335	1,712	391
Number of Dep. Dates		315	217	103	372	304	343	351	335	285	371
Number of Obs.		170,795	25,825	13,448	52,716	35,746	110,780	76,854	40,059	200,018	44,405

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 19: Demand Results Summary Table

Route		21	22	23	24	25	26	27	28	29	30
Parameter											
Leis. Price Sens.	α_L	-1.749	-1.615	-2.910	-1.158	-2.643	-1.128	-2.244	-0.774	-1.005	-1.523
		(0.096)	(0.140)	(0.079)	(0.217)	(0.079)	(0.106)	(0.046)	(0.046)	(0.114)	(0.162)
Bus. Price Sens.	α_B	-0.215	-0.019	-1.029	-0.100	-0.506	-0.158	-0.221	-0.161	-0.211	-0.126
		(0.028)	(0.004)	(0.091)	(0.019)	(0.024)	(0.032)	(0.028)	(0.024)	(0.059)	(0.025)
DoW Prefs	Mon.	0.241	–	-0.155	–	0.688	-0.233	–	0.091	-0.071	0.107
		(0.110)	–	(0.078)	–	(0.083)	(0.080)	–	(0.051)	(0.061)	(0.050)
	Tues.	-0.090	-0.207	–	-0.140	0.622	-0.250	-0.133	-0.086	-0.157	-0.019
		(0.117)	(0.055)	–	(0.086)	(0.080)	(0.089)	(0.040)	(0.061)	(0.069)	(0.059)
	Wed.	-0.052	-0.311	0.066	-0.163	0.280	-0.130	0.029	-0.057	-0.011	0.154
		(0.107)	(0.059)	(0.093)	(0.089)	(0.116)	(0.089)	(0.055)	(0.057)	(0.057)	(0.054)
	Thurs.	0.073	-0.377	-0.123	-0.384	0.045	–	-0.135	-0.015	-0.040	0.092
		(0.105)	(0.058)	(0.082)	(0.085)	(0.071)	–	(0.048)	(0.057)	(0.054)	(0.052)
	Fri.	–	-0.474	-0.111	-0.298	-0.013	-0.139	-0.402	–	-0.140	–
		–	(0.058)	(0.085)	(0.077)	(0.078)	(0.088)	(0.049)	–	(0.051)	–
	Sat.	0.108	-0.446	0.165	-0.484	–	-0.284	-0.365	-0.069	-0.055	-0.378
		(0.126)	(0.056)	(0.093)	(0.095)	–	(0.085)	(0.038)	(0.058)	(0.068)	(0.061)
	Sun.	-0.075	0.005	0.535	-0.052	0.388	0.259	-0.063	0.343	–	-0.090
		(0.097)	(0.057)	(0.098)	(0.083)	(0.076)	(0.084)	(0.055)	(0.054)	–	(0.057)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.334	0.699	0.143	0.307	0.458	0.340	0.528	0.376	0.320	0.683
Summary											
Percent. of 0s		90.4	88.6	95.5	92.2	94.8	90.9	92.9	90.3	92.9	92.5
First stage R^2		0.691	0.632	0.880	0.780	0.705	0.612	0.728	0.748	0.781	0.844
Arrivals	A	0.599	1.859	0.572	0.682	0.925	0.969	1.806	1.614	1.549	1.870
Emp. Q	Q	0.134	0.222	0.093	0.198	0.242	0.120	0.549	0.315	0.307	0.332
		(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,3.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.132	0.220	0.094	0.194	0.244	0.119	0.550	0.316	0.310	0.337
		(0.01,0.51)	(0.04,0.65)	(0.01,0.38)	(0.02,0.67)	(0.02,0.86)	(0.02,0.35)	(0.03,2.17)	(0.04,0.92)	(0.05,0.91)	(0.05,1.02)
Elas	e	-1.335	-0.102	-1.628	-1.066	-1.174	-0.896	-0.612	-0.866	-1.056	-0.371
		(-2.12,-0.28)	(-0.14,-0.06)	(-1.92,-0.74)	(-1.73,-0.19)	(-1.47,-0.75)	(-1.50,-0.35)	(-0.93,-0.33)	(-1.40,-0.34)	(-1.53,-0.48)	(-0.50,-0.25)
Number of Flights		259	517	671	752	1,152	364	1,660	792	983	1,004
Number of Dep. Dates		258	394	393	387	298	347	279	322	307	308
Number of Obs.		30,531	61,710	80,066	89,341	135,404	41,459	195,980	91,287	116,084	118,320

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 20: Demand Results Summary Table

Route		31	32	33	34	35	36	37	38	39	40
Parameter											
Leis. Price Sens.	α_L	-2.452	-0.936	-0.595	-0.989	-1.876	-1.845	-2.665	-0.931	-2.331	-1.572
		(0.159)	(0.050)	(0.044)	(0.031)	(0.066)	(0.246)	(0.109)	(0.033)	(0.045)	(0.206)
Bus. Price Sens.	α_B	-0.186	-0.237	-0.159	-0.026	-0.228	-0.090	-0.581	-0.240	-0.314	-0.576
		(0.035)	(0.029)	(0.033)	(0.005)	(0.035)	(0.017)	(0.073)	(0.017)	(0.025)	(0.074)
DoW Prefs	Mon.	0.207	–	-0.041	-0.112	–	0.009	0.176	0.123	–	-0.101
		(0.109)	–	(0.058)	(0.052)	–	(0.068)	(0.115)	(0.056)	–	(0.088)
	Tues.	-0.026	-0.228	-0.228	-0.184	-0.237	–	0.123	-0.058	0.050	-0.008
		(0.076)	(0.053)	(0.057)	(0.054)	(0.105)	–	(0.136)	(0.053)	(0.100)	(0.083)
	Wed.	–	-0.372	-0.165	–	-0.260	0.002	–	–	-0.038	0.095
		–	(0.070)	(0.061)	–	(0.104)	(0.072)	–	–	(0.086)	(0.081)
	Thurs.	-0.185	-0.274	-0.189	0.083	-0.486	-0.004	-0.174	-0.059	-0.090	0.020
		(0.081)	(0.065)	(0.059)	(0.053)	(0.072)	(0.059)	(0.108)	(0.051)	(0.096)	(0.075)
	Fri.	-0.701	-0.368	-0.246	0.189	-0.435	0.012	-0.058	-0.082	-0.165	–
		(0.083)	(0.060)	(0.062)	(0.052)	(0.062)	(0.065)	(0.105)	(0.052)	(0.073)	–
	Sat.	-0.542	-0.473	-0.272	0.798	-0.603	-0.067	-0.050	-0.212	-0.484	-0.121
		(0.087)	(0.068)	(0.064)	(0.057)	(0.090)	(0.068)	(0.119)	(0.054)	(0.106)	(0.093)
	Sun.	-0.198	0.063	–	0.337	-0.015	0.150	0.257	0.232	-0.100	0.139
		(0.074)	(0.068)	–	(0.053)	(0.081)	(0.069)	(0.120)	(0.052)	(0.076)	(0.076)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.606	0.220	0.306	0.015	0.444	0.600	0.174	0.401	0.444	0.294
Summary											
Percent. of 0s		94.3	92.1	91.1	86.5	94.5	91.8	95.7	90.6	94.0	92.3
First stage R^2		0.682	0.721	0.746	0.654	0.739	0.740	0.736	0.764	0.720	0.846
Arrivals	A	0.682	1.161	1.174	6.801	0.603	1.516	0.275	1.787	1.000	1.051
Emp. Q	Q	0.194	0.282	0.225	0.300	0.181	0.255	0.101	0.255	0.250	0.232
		(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.194	0.282	0.225	0.320	0.180	0.257	0.100	0.257	0.250	0.231
		(0.01,0.68)	(0.04,0.86)	(0.03,0.68)	(0.07,1.16)	(0.01,0.62)	(0.04,0.76)	(0.00,0.47)	(0.04,0.72)	(0.03,0.79)	(0.02,0.84)
Elas	e	-0.446	-1.260	-0.836	-3.180	-0.878	-0.341	-2.115	-1.061	-0.883	-1.554
		(-0.60,-0.26)	(-2.06,-0.56)	(-1.47,-0.25)	(-5.11,-0.97)	(-1.36,-0.40)	(-0.56,-0.15)	(-3.50,-0.45)	(-1.67,-0.45)	(-1.20,-0.57)	(-2.53,-0.64)
Number of Flights		807	836	713	394	941	729	721	772	952	516
Number of Dep. Dates		276	309	373	389	354	311	365	386	279	221
Number of Obs.		95,441	98,207	84,575	47,069	111,049	85,158	85,695	91,643	110,327	58,546

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 21: Demand Results Summary Table

Route		41	42	43	44	45	46	47	48	49	50
Parameter											
Leis. Price Sens.	α_L	-0.896	-3.251	-0.897	-2.179	-1.949	-0.359	-1.097	-2.858	-2.570	-1.659
		(0.043)	(0.094)	(0.036)	(0.050)	(0.110)	(0.069)	(0.082)	(0.080)	(0.212)	(0.055)
Bus. Price Sens.	α_B	-0.169	-0.117	-0.125	-0.110	-0.403	-0.218	-0.163	-0.575	-0.122	-0.060
		(0.037)	(0.019)	(0.017)	(0.024)	(0.043)	(0.039)	(0.028)	(0.018)	(0.026)	(0.014)
DoW Prefs	Mon.	0.266	-0.033	-0.030	0.109	0.175	-0.134	-0.084	-0.115	-0.118	1.930
		(0.077)	(0.065)	(0.056)	(0.050)	(0.055)	(0.072)	(0.068)	(0.030)	(0.140)	(0.107)
	Tues.	0.032	0.165	-0.100	0.245	0.261	-0.378	-0.120	-0.010	–	0.520
		(0.078)	(0.060)	(0.060)	(0.058)	(0.069)	(0.072)	(0.077)	(0.034)	–	(0.097)
	Wed.	0.153	0.132	-0.034	0.247	0.225	-0.233	0.044	0.160	0.174	0.172
		(0.080)	(0.042)	(0.054)	(0.044)	(0.072)	(0.065)	(0.074)	(0.041)	(0.092)	(0.086)
	Thurs.	-0.020	0.032	0.047	0.128	0.186	0.041	0.110	0.277	0.119	-0.031
		(0.073)	(0.046)	(0.056)	(0.054)	(0.056)	(0.064)	(0.071)	(0.039)	(0.131)	(0.087)
	Fri.	–	-0.246	-0.019	-0.046	0.286	–	-0.033	0.004	-0.258	–
		–	(0.045)	(0.048)	(0.041)	(0.057)	–	(0.078)	(0.032)	(0.109)	–
	Sat.	-0.187	-0.201	-0.138	-0.165	–	0.087	–	-0.125	-0.522	-0.201
		(0.075)	(0.055)	(0.054)	(0.050)	–	(0.066)	–	(0.036)	(0.116)	(0.127)
	Sun.	0.392	–	–	–	0.170	-0.186	0.044	–	-0.264	-0.211
		(0.079)	–	–	–	(0.055)	(0.063)	(0.071)	–	(0.101)	(0.089)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.298	0.578	0.292	0.524	0.392	0.482	0.368	0.360	0.495	0.318
Summary											
Percent. of 0s		88.6	92.9	90.4	92.2	90.8	84.3	90.3	86.3	90.6	83.4
First stage R^2		0.775	0.741	0.793	0.735	0.853	0.733	0.630	0.786	0.776	0.800
Arrivals	A	0.899	1.810	1.593	2.220	1.854	3.561	1.063	5.636	0.791	0.983
Emp. Q	Q	0.170	0.553	0.302	0.419	0.578	0.310	0.244	1.238	0.330	0.316
		(0.00,1.00)	(0.00,3.00)	(0.00,2.00)	(0.00,2.00)	(0.00,3.00)	(0.00,2.00)	(0.00,2.00)	(0.00,6.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.165	0.551	0.303	0.422	0.582	0.311	0.242	1.240	0.325	0.290
		(0.02,0.56)	(0.02,2.12)	(0.04,0.89)	(0.04,1.43)	(0.04,2.22)	(0.08,1.10)	(0.02,0.86)	(0.12,4.38)	(0.01,1.43)	(0.02,1.17)
Elas	e	-0.935	-0.267	-0.979	-0.364	-0.987	-0.879	-0.702	-1.420	-0.538	-1.303
		(-1.84,-0.22)	(-0.40,-0.16)	(-1.65,-0.30)	(-0.50,-0.21)	(-1.41,-0.47)	(-1.35,-0.42)	(-1.31,-0.23)	(-1.83,-0.90)	(-0.97,-0.15)	(-3.10,-0.11)
Number of Flights		390	1,641	876	1,462	1,387	221	659	1,703	559	333
Number of Dep. Dates		390	276	375	359	301	221	355	284	214	333
Number of Obs.		46,582	194,693	103,754	173,340	162,964	26,363	77,914	204,289	66,438	39,701

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 22: Demand Results Summary Table

Route		51	52	53	54	55	56	57	58	59
Parameter										
Leis. Price Sens.	α_L	-2.846	-2.301	-0.260	-0.847	-1.638	-0.583	-1.674	-1.935	-2.187
		(0.174)	(0.220)	(0.016)	(0.372)	(0.074)	(0.099)	(0.107)	(0.123)	(0.079)
Bus. Price Sens.	α_B	-0.293	-0.274	-0.090	-0.111	-0.115	-0.223	-0.182	-0.274	-0.604
		(0.034)	(0.041)	(0.010)	(0.048)	(0.025)	(0.033)	(0.037)	(0.052)	(0.030)
DoW Prefs	Mon.	-0.246	0.023	-0.242	-0.004	–	0.082	0.292	0.210	0.566
		(0.089)	(0.107)	(0.048)	(0.092)	–	(0.112)	(0.094)	(0.107)	(0.088)
	Tues.	–	-0.109	-0.179	0.182	-0.020	-0.042	0.005	-0.052	0.579
		–	(0.119)	(0.047)	(0.094)	(0.062)	(0.108)	(0.090)	(0.120)	(0.081)
	Wed.	0.256	0.093	-0.198	0.108	0.041	0.190	-0.061	–	0.445
		(0.116)	(0.110)	(0.048)	(0.089)	(0.056)	(0.100)	(0.089)	–	(0.103)
	Thurs.	-0.032	-0.026	-0.143	-0.050	0.150	0.242	–	0.108	0.184
		(0.109)	(0.120)	(0.048)	(0.116)	(0.059)	(0.095)	–	(0.108)	(0.067)
	Fri.	-0.091	-0.138	-0.040	–	-0.033	0.078	-0.312	-0.032	–
		(0.080)	(0.111)	(0.042)	–	(0.064)	(0.102)	(0.085)	(0.117)	–
	Sat.	-0.298	-0.135	–	-0.109	-0.024	-0.050	-0.313	-0.088	-0.035
		(0.129)	(0.097)	–	(0.111)	(0.063)	(0.084)	(0.097)	(0.142)	(0.079)
	Sun.	-0.445	–	-0.060	0.382	0.029	–	0.361	0.458	0.172
		(0.100)	–	(0.044)	(0.092)	(0.077)	–	(0.089)	(0.121)	(0.062)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.427	0.728	0.281	0.392	0.731	0.540	0.430	0.405	0.346
Summary										
Percent. of 0s		95.4	93.0	81.3	85.1	93.8	93.6	89.8	89.9	95.3
First stage R^2		0.751	0.809	0.669	0.569	0.763	0.763	0.794	0.740	0.708
Arrivals	A	0.599	3.126	6.387	3.884	4.800	2.707	0.837	0.577	0.657
Emp. Q	Q	0.164	0.115	0.369	0.262	0.193	0.115	0.143	0.142	0.166
		(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)
Model Q	$E[Q]$	0.164	0.121	0.379	0.264	0.211	0.122	0.142	0.141	0.166
		(0.01,0.71)	(0.02,0.31)	(0.13,1.26)	(0.08,0.82)	(0.04,0.67)	(0.03,0.31)	(0.01,0.51)	(0.01,0.55)	(0.01,0.71)
Elas	e	-0.709	-0.772	-0.876	-1.132	-0.383	-0.956	-0.880	-1.247	-1.581
		(-0.98,-0.45)	(-1.30,-0.52)	(-1.32,-0.57)	(-1.51,-0.64)	(-0.59,-0.28)	(-1.60,-0.58)	(-1.50,-0.20)	(-2.03,-0.32)	(-1.90,-0.94)
Number of Flights		854	96	396	107	374	145	311	260	927
Number of Dep. Dates		291	96	396	107	194	117	311	260	317
Number of Obs.		100,922	11,463	47,336	12,774	44,311	15,440	36,570	30,454	109,772

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 23: Demand Results Summary Table

Route		60	61	62	63	64	65	66	67	68
Parameter										
Leis. Price Sens.	α_L	-0.875	-1.579	-1.936	-0.975	-1.495	-1.987	-2.122	-1.304	-0.641
		(0.225)	(0.212)	(0.038)	(0.126)	(0.057)	(0.082)	(0.131)	(0.061)	(0.065)
Bus. Price Sens.	α_B	-0.257	-0.436	-0.751	-0.213	-0.165	-0.384	-0.397	-0.219	-0.235
		(0.051)	(0.035)	(0.033)	(0.055)	(0.029)	(0.052)	(0.068)	(0.030)	(0.025)
DoW Prefs	Mon.	–	-0.350	0.181	–	0.172	0.631	0.035	0.771	-0.319
		–	(0.170)	(0.089)	–	(0.119)	(0.107)	(0.160)	(0.127)	(0.085)
	Tues.	-0.218	-0.684	0.064	-0.098	-0.003	0.418	–	0.436	-0.319
		(0.118)	(0.164)	(0.095)	(0.095)	(0.092)	(0.081)	–	(0.129)	(0.078)
	Wed.	0.159	–	0.053	0.082	–	0.573	-0.181	0.418	–
		(0.112)	–	(0.089)	(0.100)	–	(0.122)	(0.134)	(0.091)	–
	Thurs.	-0.093	0.040	-0.206	0.050	0.824	0.216	-0.284	-0.041	-0.011
		(0.109)	(0.156)	(0.068)	(0.095)	(0.070)	(0.100)	(0.125)	(0.092)	(0.074)
	Fri.	0.047	-0.166	-0.695	-0.216	0.353	–	-0.587	-0.095	-0.163
		(0.116)	(0.158)	(0.064)	(0.090)	(0.075)	–	(0.107)	(0.101)	(0.076)
	Sat.	-0.043	-0.101	-0.624	-0.299	0.520	-0.258	-0.405	–	-0.287
		(0.112)	(0.130)	(0.085)	(0.096)	(0.167)	(0.108)	(0.158)	–	(0.080)
	Sun.	-0.199	-0.323	–	0.397	0.272	0.251	0.212	0.482	-0.139
		(0.109)	(0.140)	–	(0.105)	(0.155)	(0.081)	(0.136)	(0.135)	(0.080)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.925	0.872	0.210	0.216	0.500	0.514	0.198	0.264	0.602
Summary										
Percent. of 0s		93.4	93.1	92.5	90.1	96.4	96.1	96.3	94.2	93.0
First stage R^2		0.726	0.686	0.703	0.799	0.736	0.700	0.623	0.695	0.780
Arrivals	A	3.062	4.616	1.224	0.876	0.396	0.336	0.255	0.884	3.508
Emp. Q	Q	0.117	0.142	0.474	0.136	0.230	0.130	0.096	0.340	0.119
		(0.00,1.00)	(0.00,1.00)	(0.00,3.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)
Model Q	$E[Q]$	0.125	0.155	0.469	0.136	0.220	0.130	0.095	0.333	0.126
		(0.02,0.33)	(0.03,0.39)	(0.02,2.08)	(0.01,0.50)	(0.00,1.03)	(0.00,0.63)	(0.00,0.49)	(0.02,1.39)	(0.03,0.32)
Elas	e	-0.669	-1.387	-2.143	-0.964	-1.035	-0.970	-1.715	-1.379	-0.886
		(-0.99,-0.47)	(-2.90,-0.87)	(-3.16,-1.11)	(-1.75,-0.32)	(-2.70,-0.18)	(-1.47,-0.48)	(-2.43,-0.60)	(-2.21,-0.41)	(-1.36,-0.51)
Number of Flights		117	53	1,120	283	709	965	671	602	211
Number of Dep. Dates		117	53	236	277	131	351	302	133	205
Number of Obs.		13,960	6,342	129,887	32,711	83,245	114,462	79,617	70,103	25,005

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 24: Demand Results Summary Table

Route		69	70	71	72	73	74	75	76	77
Parameter										
Leis. Price Sens.	α_L	-1.145	-0.974	-2.039	-2.553	-1.390	-2.076	-1.085	-1.015	-1.572
		(0.047)	(0.085)	(0.053)	(0.037)	(0.040)	(0.046)	(0.332)	(0.109)	(0.092)
Bus. Price Sens.	α_B	-0.070	-0.245	-0.205	-0.254	-0.075	-0.061	-0.284	-0.123	-0.336
		(0.016)	(0.046)	(0.033)	(0.037)	(0.016)	(0.011)	(0.033)	(0.029)	(0.051)
DoW Prefs	Mon.	0.306	0.045	-0.072	–	-0.147	0.144	-0.360	0.024	-0.118
		(0.060)	(0.072)	(0.095)	–	(0.066)	(0.049)	(0.186)	(0.066)	(0.090)
	Tues.	0.168	0.210	–	-0.204	-0.105	-0.059	-0.335	-0.146	0.146
		(0.066)	(0.091)	–	(0.103)	(0.066)	(0.055)	(0.182)	(0.077)	(0.086)
	Wed.	–	0.188	-0.083	-0.285	-0.170	0.066	0.270	-0.143	0.109
		–	(0.073)	(0.091)	(0.090)	(0.101)	(0.060)	(0.169)	(0.078)	(0.103)
	Thurs.	-0.041	0.050	-0.081	-0.635	-0.100	–	-0.010	-0.156	–
		(0.058)	(0.062)	(0.104)	(0.095)	(0.065)	–	(0.173)	(0.070)	–
	Fri.	-0.262	–	-0.205	-1.010	–	0.058	-0.162	-0.153	-0.227
		(0.052)	–	(0.093)	(0.085)	–	(0.061)	(0.166)	(0.071)	(0.079)
	Sat.	-0.270	0.016	-0.458	-0.920	0.327	-0.196	–	-0.278	-0.405
		(0.062)	(0.085)	(0.094)	(0.096)	(0.071)	(0.058)	–	(0.073)	(0.078)
	Sun.	0.338	0.400	-0.093	-0.181	-0.162	0.040	-0.130	–	-0.509
		(0.058)	(0.066)	(0.088)	(0.136)	(0.101)	(0.062)	(0.108)	–	(0.072)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.375	0.223	0.382	0.420	0.049	0.751	0.932	0.936	0.267
Summary										
Percent. of 0s		88.8	93.0	95.1	92.4	78.8	92.5	91.8	90.8	92.7
First stage R^2		0.788	0.655	0.735	0.745	0.437	0.830	0.789	0.780	0.670
Arrivals	A	2.067	0.859	1.679	1.308	2.806	1.808	3.293	3.018	1.131
Emp. Q	Q	0.319	0.180	0.179	0.394	0.402	0.339	0.149	0.188	0.461
		(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,3.00)
Model Q	$E[Q]$	0.317	0.178	0.182	0.387	0.400	0.343	0.158	0.194	0.455
		(0.04,1.00)	(0.01,0.63)	(0.01,0.67)	(0.02,1.56)	(0.03,1.49)	(0.06,1.03)	(0.04,0.42)	(0.04,0.60)	(0.02,2.08)
Elas	e	-0.777	-1.179	-0.677	-0.815	-2.771	-0.179	-1.117	-0.411	-1.438
		(-1.28,-0.14)	(-1.66,-0.51)	(-0.85,-0.46)	(-1.22,-0.39)	(-4.71,-1.38)	(-0.24,-0.10)	(-1.92,-0.71)	(-0.55,-0.32)	(-2.17,-0.50)
Number of Flights		597	636	630	898	301	1,011	51	266	966
Number of Dep. Dates		303	313	226	230	301	307	51	208	204
Number of Obs.		68,698	70,651	71,472	104,037	35,989	118,859	6,086	31,374	111,843

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 25: Demand Results Summary Table

Route		78	79	80	81	82	83	84	85	86
Parameter										
Leis. Price Sens.	α_L	-1.037	-1.274	-0.662	-0.942	-1.801	-1.487	-1.213	-1.615	-0.722
		(0.090)	(0.047)	(0.045)	(0.051)	(0.055)	(0.144)	(0.123)	(0.036)	(0.103)
Bus. Price Sens.	α_B	-0.285	-0.056	-0.098	-0.186	-0.438	-0.639	-0.203	-0.157	-0.357
		(0.048)	(0.012)	(0.027)	(0.035)	(0.049)	(0.109)	(0.039)	(0.026)	(0.082)
DoW Prefs	Mon.	0.149	-0.090	0.041	-0.088	-0.102	–	–	-0.212	-0.036
		(0.049)	(0.062)	(0.047)	(0.078)	(0.069)	–	–	(0.118)	(0.048)
	Tues.	0.021	-0.087	0.203	–	-0.082	0.137	-0.232	-0.692	0.008
		(0.052)	(0.064)	(0.044)	–	(0.074)	(0.106)	(0.098)	(0.160)	(0.055)
	Wed.	-0.020	-0.375	0.208	0.121	-0.035	0.161	-0.276	-0.410	–
		(0.050)	(0.097)	(0.053)	(0.084)	(0.067)	(0.101)	(0.099)	(0.096)	–
	Thurs.	0.024	-0.023	0.078	0.028	–	0.385	-0.392	-0.220	-0.019
		(0.049)	(0.061)	(0.041)	(0.074)	–	(0.091)	(0.094)	(0.130)	(0.051)
	Fri.	-0.002	–	-0.112	-0.031	-0.047	0.365	-0.230	-0.725	0.441
		(0.051)	–	(0.035)	(0.077)	(0.078)	(0.096)	(0.095)	(0.096)	(0.107)
	Sat.	–	0.238	-0.213	-0.383	-0.392	-0.190	-0.301	-0.387	0.614
		–	(0.076)	(0.048)	(0.080)	(0.058)	(0.100)	(0.101)	(0.160)	(0.122)
	Sun.	0.271	-0.002	–	0.219	-0.107	0.010	-0.330	–	0.447
		(0.051)	(0.094)	–	(0.084)	(0.075)	(0.096)	(0.094)	–	(0.105)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.179	0.047	0.256	0.169	0.227	0.264	0.322	0.444	0.052
Summary										
Percent. of 0s		84.6	77.4	88.9	89.5	95.2	90.4	90.9	96.6	95.0
First stage R^2		0.825	0.443	0.743	0.830	0.664	0.891	0.756	0.746	0.643
Arrivals	A	2.509	2.938	2.390	1.068	0.654	0.780	0.818	0.393	3.946
Emp. Q	Q	0.293	0.441	0.642	0.165	0.189	0.154	0.124	0.222	0.168
		(0.00,2.00)	(0.00,3.00)	(0.00,3.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.295	0.440	0.642	0.160	0.191	0.151	0.123	0.209	0.187
		(0.04,1.06)	(0.03,1.66)	(0.06,2.40)	(0.02,0.54)	(0.02,0.72)	(0.01,0.60)	(0.01,0.42)	(0.00,1.03)	(0.05,0.50)
Elas	e	-1.285	-2.665	-0.603	-1.003	-1.664	-1.097	-0.910	-1.107	-3.117
		(-2.11,-0.59)	(-4.88,-1.31)	(-0.96,-0.18)	(-1.84,-0.38)	(-2.15,-0.70)	(-1.54,-0.56)	(-1.54,-0.34)	(-2.53,-0.18)	(-4.01,-2.10)
Number of Flights		489	301	1,371	391	1,219	310	282	679	632
Number of Dep. Dates		394	301	346	385	366	291	275	125	345
Number of Obs.		58,278	35,965	161,536	46,185	144,519	36,602	32,588	79,820	75,464

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 26: Demand Results Summary Table

Route		87	88	89	90	91	92	93	94	95
Parameter										
Leis. Price Sens.	α_L	-2.610	-1.025	-2.163	-2.930	-2.717	-2.341	-1.943	-0.443	-1.459
		(0.106)	(0.088)	(0.054)	(0.157)	(0.168)	(0.052)	(0.076)	(0.074)	(0.078)
Bus. Price Sens.	α_B	-0.193	-0.229	-0.308	-0.355	-0.301	-0.208	-0.101	-0.147	-0.171
		(0.025)	(0.049)	(0.023)	(0.059)	(0.038)	(0.039)	(0.023)	(0.025)	(0.031)
DoW Prefs	Mon.	-0.265	–	0.079	0.496	-0.056	0.304	-0.113	0.161	–
		(0.079)	–	(0.045)	(0.148)	(0.113)	(0.135)	(0.048)	(0.074)	–
	Tues.	0.048	-0.027	0.091	0.139	0.188	–	-0.035	-0.107	0.062
		(0.104)	(0.077)	(0.058)	(0.125)	(0.126)	–	(0.059)	(0.075)	(0.150)
	Wed.	0.050	-0.042	0.184	0.449	0.662	0.164	–	0.020	-0.118
		(0.099)	(0.072)	(0.051)	(0.110)	(0.221)	(0.132)	–	(0.079)	(0.142)
	Thurs.	–	0.113	-0.031	0.364	0.294	-0.102	-0.139	0.001	-0.096
		–	(0.066)	(0.046)	(0.134)	(0.086)	(0.113)	(0.050)	(0.078)	(0.136)
	Fri.	-0.231	-0.009	–	-0.123	0.359	0.030	-0.327	–	-0.081
		(0.084)	(0.064)	–	(0.144)	(0.093)	(0.111)	(0.045)	–	(0.129)
	Sat.	-0.444	-0.125	-0.172	-0.042	-0.073	-0.234	-0.303	0.164	-0.559
		(0.083)	(0.066)	(0.049)	(0.165)	(0.103)	(0.109)	(0.054)	(0.084)	(0.144)
	Sun.	-0.645	0.106	-0.035	–	–	-0.088	-0.238	0.460	0.126
		(0.084)	(0.072)	(0.048)	–	–	(0.112)	(0.043)	(0.085)	(0.109)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.551	0.213	0.412	0.350	0.394	0.330	0.713	0.389	0.373
Summary										
Percent. of 0s		94.6	92.5	94.4	96.2	94.3	93.7	89.8	93.1	95.4
First stage R^2		0.612	0.722	0.685	0.632	0.647	0.730	0.769	0.805	0.621
Arrivals	A	0.663	1.168	1.315	0.252	0.858	0.525	2.244	2.900	0.362
Emp. Q	Q	0.187	0.266	0.297	0.098	0.333	0.156	0.554	0.117	0.112
		(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,3.00)	(0.00,1.00)	(0.00,1.00)
Model Q	$E[Q]$	0.186	0.265	0.299	0.097	0.324	0.153	0.555	0.123	0.110
		(0.01,0.68)	(0.03,0.83)	(0.03,1.13)	(0.00,0.48)	(0.01,1.41)	(0.01,0.61)	(0.05,2.05)	(0.03,0.31)	(0.01,0.36)
Elas	e	-0.480	-1.297	-0.857	-1.168	-1.032	-1.094	-0.270	-0.779	-1.043
		(-0.68,-0.28)	(-2.21,-0.50)	(-1.04,-0.58)	(-1.77,-0.43)	(-1.88,-0.49)	(-1.90,-0.34)	(-0.38,-0.14)	(-1.34,-0.44)	(-1.58,-0.34)
Number of Flights		846	751	1,546	595	574	621	1,403	209	478
Number of Dep. Dates		290	267	358	278	129	306	355	203	232
Number of Obs.		100,155	83,444	181,578	70,797	67,011	72,946	163,706	24,674	54,815

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 27: Demand Results Summary Table

Route		96	97	98	99	100	101	102	103	104
Parameter										
Leis. Price Sens.	α_L	-0.854	-1.145	-2.311	-2.939	-0.691	-0.829	-0.254	-0.650	-1.527
		(0.036)	(0.137)	(0.268)	(0.185)	(0.159)	(0.039)	(0.008)	(0.033)	(0.093)
Bus. Price Sens.	α_B	-0.237	-0.214	-1.027	-0.338	-0.227	-0.089	-0.218	-0.079	-0.258
		(0.025)	(0.092)	(0.193)	(0.032)	(0.028)	(0.019)	(0.006)	(0.016)	(0.037)
DoW Prefs	Mon.	–	0.691	-0.368	0.386	-0.490	-0.622	–	0.052	0.128
		–	(0.096)	(0.085)	(0.114)	(0.088)	(0.095)	–	(0.047)	(0.113)
	Tues.	-0.202	0.676	-0.039	0.089	-0.308	-0.524	-0.213	-0.075	0.431
		(0.050)	(0.100)	(0.109)	(0.087)	(0.093)	(0.093)	(0.076)	(0.052)	(0.105)
	Wed.	-0.115	0.283	0.069	–	-0.356	-0.104	-0.111	-0.143	0.220
		(0.053)	(0.061)	(0.093)	–	(0.087)	(0.088)	(0.076)	(0.045)	(0.121)
	Thurs.	-0.096	0.118	-0.023	-0.047	–	0.075	0.020	-0.196	0.186
		(0.045)	(0.056)	(0.083)	(0.106)	–	(0.090)	(0.058)	(0.042)	(0.103)
	Fri.	0.044	–	–	-0.169	-0.098	–	0.029	-0.235	0.187
		(0.052)	–	–	(0.088)	(0.080)	–	(0.057)	(0.043)	(0.088)
	Sat.	-0.226	-0.244	-0.297	-0.321	-0.430	-0.165	0.235	-0.417	-0.153
		(0.046)	(0.061)	(0.098)	(0.107)	(0.076)	(0.091)	(0.053)	(0.046)	(0.111)
	Sun.	0.029	0.411	-0.001	0.063	-0.194	-0.266	0.161	–	–
		(0.050)	(0.074)	(0.090)	(0.092)	(0.078)	(0.089)	(0.057)	–	–
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.333	0.357	0.227	0.587	0.922	0.047	0.478	0.285	0.618
Summary										
Percent. of 0s		89.8	91.5	92.9	92.1	91.2	92.1	85.5	87.3	94.4
First stage R^2		0.773	0.764	0.703	0.870	0.854	0.812	0.669	0.750	0.788
Arrivals	A	2.062	0.974	0.542	0.945	2.834	1.745	7.678	3.962	0.580
Emp. Q	Q	0.527	0.310	0.098	0.315	0.161	0.146	0.353	0.667	0.222
		(0.00,3.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,3.00)	(0.00,2.00)
Model Q	$E[Q]$	0.525	0.305	0.096	0.311	0.167	0.147	0.372	0.675	0.221
		(0.07,1.50)	(0.02,1.03)	(0.01,0.35)	(0.02,1.12)	(0.04,0.48)	(0.03,0.40)	(0.09,1.39)	(0.14,1.82)	(0.03,0.68)
Elas	e	-0.961	-1.230	-1.709	-0.660	-0.619	-1.778	-1.188	-0.676	-0.768
		(-1.72,-0.39)	(-2.22,-0.39)	(-2.36,-0.74)	(-0.94,-0.27)	(-1.45,-0.41)	(-2.91,-1.09)	(-1.92,-0.76)	(-1.25,-0.17)	(-1.10,-0.42)
Number of Flights		1,027	927	393	698	179	191	217	842	776
Number of Dep. Dates		286	330	392	228	171	177	217	245	221
Number of Obs.		118,307	105,706	46,999	80,735	20,705	22,749	25,914	94,552	86,314

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 28: Demand Results Summary Table

Route		105	106	107	108	109	110	111	112	113
Parameter										
Leis. Price Sens.	α_L	-2.079	-0.924	-0.889	-0.799	-2.386	-2.921	-1.763	-0.742	-0.720
		(0.102)	(0.057)	(0.064)	(0.053)	(0.068)	(0.106)	(0.084)	(0.042)	(0.026)
Bus. Price Sens.	α_B	-0.116	-0.122	-0.154	-0.120	-0.084	-0.349	-0.062	-0.090	-0.110
		(0.025)	(0.028)	(0.024)	(0.026)	(0.025)	(0.059)	(0.018)	(0.022)	(0.018)
DoW Prefs	Mon.	0.021	-0.090	–	0.282	-0.158	-0.100	0.021	-0.020	0.134
		(0.118)	(0.086)	–	(0.078)	(0.039)	(0.122)	(0.060)	(0.044)	(0.052)
	Tues.	-0.243	-0.090	-0.014	0.238	–	0.028	-0.015	–	–
		(0.082)	(0.102)	(0.062)	(0.079)	–	(0.151)	(0.070)	–	–
	Wed.	–	–	0.019	0.199	0.026	-0.232	0.079	0.178	0.003
		–	–	(0.061)	(0.080)	(0.044)	(0.108)	(0.063)	(0.052)	(0.055)
	Thurs.	0.269	0.118	-0.028	0.210	-0.087	–	0.172	0.195	0.088
		(0.080)	(0.086)	(0.065)	(0.075)	(0.040)	–	(0.069)	(0.055)	(0.052)
	Fri.	0.199	0.106	-0.010	0.226	-0.198	-0.056	0.263	0.231	0.122
		(0.096)	(0.083)	(0.062)	(0.072)	(0.040)	(0.146)	(0.061)	(0.046)	(0.052)
	Sat.	-0.395	-0.228	-0.111	–	-0.469	-0.663	–	-0.239	-0.037
		(0.096)	(0.084)	(0.058)	–	(0.049)	(0.136)	–	(0.041)	(0.050)
	Sun.	-0.012	-0.125	0.093	0.698	-0.234	-0.436	-0.210	0.108	0.076
		(0.072)	(0.083)	(0.055)	(0.077)	(0.041)	(0.165)	(0.061)	(0.047)	(0.055)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.430	0.247	0.340	0.127	0.546	0.294	0.458	0.359	0.355
Summary										
Percent. of 0s		94.5	92.0	91.6	88.7	92.1	95.7	89.2	87.2	90.4
First stage R^2		0.742	0.749	0.752	0.817	0.752	0.828	0.781	0.756	0.773
Arrivals	A	0.639	0.667	1.477	1.089	2.711	0.268	1.855	3.756	1.776
Emp. Q	Q	0.180	0.110	0.256	0.179	0.488	0.102	0.291	0.670	0.264
		(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,3.00)	(0.00,1.00)	(0.00,2.00)	(0.00,3.00)	(0.00,2.00)
Model Q	$E[Q]$	0.179	0.109	0.258	0.173	0.494	0.100	0.288	0.679	0.265
		(0.01,0.63)	(0.01,0.37)	(0.04,0.76)	(0.02,0.60)	(0.05,1.65)	(0.00,0.47)	(0.03,0.92)	(0.15,1.77)	(0.04,0.75)
Elas	e	-0.596	-0.843	-0.886	-0.850	-0.269	-1.393	-0.507	-0.672	-0.754
		(-1.09,-0.22)	(-1.52,-0.19)	(-1.41,-0.29)	(-1.59,-0.28)	(-0.34,-0.16)	(-1.99,-0.29)	(-0.91,-0.11)	(-1.21,-0.17)	(-1.31,-0.24)
Number of Flights		976	396	753	381	1,528	711	582	823	767
Number of Dep. Dates		366	396	325	379	332	361	307	235	383
Number of Obs.		115,101	47,231	88,155	45,352	180,174	84,446	66,956	91,695	91,042

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 29: Demand Results Summary Table

Route		114	115	116	117	118	119	120	121	122
Parameter										
Leis. Price Sens.	α_L	-2.236	-1.825	-2.090	-2.412	-0.763	-0.464	-1.695	-0.426	-0.624
		(0.067)	(0.053)	(0.128)	(0.088)	(0.118)	(0.040)	(0.094)	(0.030)	(0.084)
Bus. Price Sens.	α_B	-0.691	-0.379	-0.518	-0.312	-0.421	-0.174	-0.250	-0.169	-0.255
		(0.031)	(0.045)	(0.029)	(0.050)	(0.064)	(0.025)	(0.049)	(0.024)	(0.075)
DoW Prefs	Mon.	–	0.242	0.231	0.105	-0.053	0.145	–	-0.106	-0.079
		–	(0.064)	(0.157)	(0.065)	(0.071)	(0.061)	–	(0.068)	(0.045)
	Tues.	0.049	0.227	0.200	0.146	-0.085	–	0.085	-0.008	-0.044
		(0.079)	(0.083)	(0.152)	(0.051)	(0.072)	–	(0.059)	(0.070)	(0.048)
	Wed.	0.106	0.182	0.362	0.047	-0.042	0.016	0.010	–	–
		(0.079)	(0.074)	(0.108)	(0.061)	(0.066)	(0.057)	(0.044)	–	–
	Thurs.	0.023	0.056	0.226	0.025	0.335	0.175	-0.037	0.254	0.070
		(0.078)	(0.092)	(0.130)	(0.050)	(0.066)	(0.058)	(0.040)	(0.060)	(0.043)
	Fri.	-0.088	-0.165	0.027	–	0.002	0.135	-0.095	0.015	0.260
		(0.069)	(0.072)	(0.117)	–	(0.058)	(0.060)	(0.044)	(0.060)	(0.075)
	Sat.	-0.245	-0.232	–	-0.330	–	-0.107	-0.252	-0.185	0.203
		(0.086)	(0.070)	–	(0.062)	–	(0.054)	(0.055)	(0.062)	(0.078)
	Sun.	-0.136	–	-0.133	0.151	-0.099	0.037	-0.008	-0.016	0.206
		(0.080)	–	(0.126)	(0.057)	(0.066)	(0.058)	(0.046)	(0.065)	(0.071)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.244	0.441	0.437	0.587	0.202	0.198	0.439	0.322	0.050
Summary										
Percent. of 0s		95.2	95.2	94.9	94.2	90.6	88.2	92.2	90.3	95.0
First stage R^2		0.648	0.712	0.707	0.758	0.729	0.627	0.745	0.795	0.562
Arrivals	A	0.676	0.681	0.528	1.073	3.194	2.617	2.364	3.521	4.564
Emp. Q	Q	0.192	0.224	0.200	0.239	0.215	0.230	0.423	0.200	0.174
		(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.193	0.225	0.199	0.240	0.222	0.234	0.429	0.208	0.195
		(0.02,0.73)	(0.02,0.88)	(0.02,0.66)	(0.03,0.80)	(0.04,0.68)	(0.04,0.74)	(0.04,1.44)	(0.04,0.63)	(0.04,0.56)
Elas	e	-2.015	-1.040	-1.448	-0.663	-1.898	-0.950	-0.844	-0.932	-2.556
		(-2.68,-1.04)	(-1.28,-0.58)	(-1.87,-0.82)	(-0.83,-0.47)	(-2.56,-1.51)	(-1.59,-0.47)	(-1.04,-0.51)	(-1.43,-0.68)	(-3.18,-1.73)
Number of Flights		1,242	1,443	687	1,314	316	452	1,298	276	671
Number of Dep. Dates		371	363	198	384	210	378	314	215	362
Number of Obs.		147,288	170,376	77,032	155,366	37,711	53,729	150,869	32,599	80,043

Note: For the “parameter” rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the “summary” rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled “Percent. of 0s”, the r-squared of a regression of prices on the controls and instruments is in “First stage R^2”, the mean of the estimated posterior distribution for the arrivals process is in “A”, the average total number of purchases observed in the data is in “Emp. Q” with the 5th and 95th percentile of purchases in parentheses, our model’s prediction of the average total number of purchases is in “Model Q” with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled “Elas”. Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 30: Demand Results Summary Table

Route		123	124	125	126	127	128	129	130	131
Parameter										
Leis. Price Sens.	α_L	-1.881	-1.109	-0.931	-1.175	-1.649	-0.409	-1.331	-1.321	-1.006
		(0.067)	(0.083)	(0.073)	(0.173)	(0.037)	(0.053)	(0.054)	(0.137)	(0.089)
Bus. Price Sens.	α_B	-0.550	-0.237	-0.117	-0.368	-0.454	-0.221	-0.141	-0.191	-0.242
		(0.036)	(0.040)	(0.029)	(0.106)	(0.067)	(0.036)	(0.027)	(0.063)	(0.053)
DoW Prefs	Mon.	-0.026	0.305	0.192	0.221	0.126	-0.264	–	0.627	0.150
		(0.053)	(0.080)	(0.099)	(0.046)	(0.142)	(0.088)	–	(0.082)	(0.075)
	Tues.	0.020	-0.059	–	0.321	0.165	-0.416	-0.392	0.467	0.171
		(0.055)	(0.088)	–	(0.049)	(0.113)	(0.097)	(0.067)	(0.088)	(0.078)
	Wed.	0.101	0.235	-0.019	0.230	0.410	-0.187	-0.462	0.056	0.173
		(0.051)	(0.083)	(0.089)	(0.047)	(0.102)	(0.084)	(0.069)	(0.064)	(0.084)
	Thurs.	–	0.404	-0.248	0.275	0.419	–	-0.252	0.304	-0.001
		–	(0.089)	(0.090)	(0.044)	(0.109)	–	(0.064)	(0.076)	(0.081)
	Fri.	-0.098	–	-0.191	0.265	0.019	-0.271	-0.589	0.324	-0.041
		(0.061)	–	(0.084)	(0.058)	(0.100)	(0.075)	(0.064)	(0.086)	(0.063)
	Sat.	-0.146	0.102	-0.317	–	–	-0.493	-0.747	–	0.033
		(0.070)	(0.080)	(0.098)	–	–	(0.084)	(0.070)	–	(0.090)
	Sun.	0.113	0.104	0.369	0.158	0.027	-0.328	0.308	0.209	–
		(0.058)	(0.089)	(0.097)	(0.055)	(0.087)	(0.085)	(0.069)	(0.082)	–
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.323	0.333	0.188	0.218	0.441	0.274	0.261	0.452	0.238
Summary										
Percent. of 0s		94.3	92.9	91.5	92.2	95.2	91.7	82.4	93.7	93.3
First stage R^2		0.677	0.834	0.785	0.742	0.741	0.779	0.800	0.713	0.652
Arrivals	A	1.368	0.823	0.667	2.802	0.684	2.082	1.560	1.028	0.784
Emp. Q	Q	0.309	0.085	0.116	0.493	0.228	0.128	0.307	0.291	0.170
		(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,3.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)
Model Q	$E[Q]$	0.314	0.086	0.114	0.503	0.229	0.131	0.297	0.288	0.168
		(0.04,1.12)	(0.02,0.23)	(0.01,0.40)	(0.06,1.69)	(0.02,0.89)	(0.01,0.41)	(0.04,1.10)	(0.03,0.87)	(0.01,0.58)
Elas	e	-1.441	-0.968	-0.944	-1.452	-1.155	-0.934	-1.455	-0.917	-1.175
		(-1.75,-1.08)	(-1.35,-0.54)	(-1.62,-0.20)	(-1.93,-0.78)	(-1.60,-0.67)	(-1.42,-0.58)	(-2.94,-0.20)	(-1.39,-0.40)	(-1.72,-0.51)
Number of Flights		1,403	371	397	1,495	1,372	196	391	790	622
Number of Dep. Dates		319	371	396	315	345	192	391	226	308
Number of Obs.		164,088	44,200	47,306	171,177	162,637	22,953	46,734	92,967	69,175

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 31: Demand Results Summary Table

Route		132	133	134	135	136	137	138	139	140
Parameter										
Leis. Price Sens.	α_L	-1.848	-2.137	-0.912	-2.261	-1.292	-2.882	-1.892	-2.745	-1.378
		(0.061)	(0.150)	(0.053)	(0.153)	(0.084)	(0.237)	(0.052)	(0.118)	(0.046)
Bus. Price Sens.	α_B	-0.665	-1.169	-0.183	-0.197	-0.085	-0.298	-0.069	-0.317	-0.149
		(0.058)	(0.127)	(0.035)	(0.034)	(0.016)	(0.041)	(0.013)	(0.064)	(0.026)
DoW Prefs	Mon.	0.090	0.440	0.158	-0.025	0.185	-0.140	-0.270	-0.266	0.229
		(0.078)	(0.090)	(0.077)	(0.072)	(0.075)	(0.069)	(0.094)	(0.089)	(0.083)
	Tues.	-0.024	0.202	0.122	-0.191	-0.073	-0.083	-0.271	0.082	–
		(0.072)	(0.098)	(0.074)	(0.081)	(0.077)	(0.107)	(0.087)	(0.091)	–
	Wed.	0.200	–	0.191	-0.219	–	–	0.362	–	-0.216
		(0.089)	–	(0.087)	(0.089)	–	–	(0.093)	–	(0.077)
	Thurs.	0.099	0.042	0.175	-0.123	0.053	0.044	1.599	0.590	0.163
		(0.078)	(0.096)	(0.076)	(0.089)	(0.078)	(0.106)	(0.128)	(0.121)	(0.079)
	Fri.	0.171	0.017	0.288	-0.161	-0.000	0.128	-0.282	-0.119	0.342
		(0.076)	(0.092)	(0.074)	(0.080)	(0.076)	(0.083)	(0.082)	(0.076)	(0.078)
	Sat.	–	-0.020	–	-0.298	-0.350	-0.205	-0.468	-0.392	-0.051
		–	(0.094)	–	(0.086)	(0.079)	(0.087)	(0.126)	(0.100)	(0.078)
	Sun.	0.131	0.092	0.247	–	0.014	-0.067	–	-0.631	-0.254
		(0.075)	(0.096)	(0.077)	–	(0.067)	(0.072)	–	(0.086)	(0.076)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.385	0.216	0.260	0.825	0.457	0.374	0.314	0.400	0.301
Summary										
Percent. of 0s		92.6	91.0	89.6	91.7	90.6	95.2	83.8	92.6	83.4
First stage R^2		0.834	0.817	0.754	0.799	0.793	0.762	0.735	0.759	0.778
Arrivals	A	1.066	0.755	0.892	2.307	1.103	1.449	0.987	1.251	1.120
Emp. Q	Q	0.221	0.146	0.155	0.127	0.244	0.170	0.283	0.397	0.283
		(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.221	0.143	0.150	0.130	0.240	0.172	0.268	0.392	0.266
		(0.02,0.79)	(0.01,0.57)	(0.02,0.51)	(0.02,0.39)	(0.04,0.68)	(0.02,0.61)	(0.02,1.06)	(0.02,1.60)	(0.04,0.91)
Elas	e	-1.485	-1.665	-0.985	-0.569	-0.719	-0.703	-1.356	-0.971	-1.304
		(-2.12,-0.72)	(-2.16,-0.98)	(-1.90,-0.25)	(-0.92,-0.42)	(-1.24,-0.16)	(-0.89,-0.53)	(-2.97,-0.12)	(-1.48,-0.46)	(-2.63,-0.16)
Number of Flights		623	318	389	191	671	718	336	794	387
Number of Dep. Dates		278	299	389	188	338	267	335	193	387
Number of Obs.		73,598	37,682	46,464	22,483	76,893	82,972	39,900	90,762	46,205

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

D.2 Demand Estimation Details

Table 32 presents details of the prior distribution choices. Table 33 presents the candidate distribution for the Metropolis-Hastings steps used in estimation.

Table 32: Prior Distribution Details

Parameter	Prior Distribution	Sampling Step	Further Details
λ	Uniform density over $\mathbb{R}$	Metropolis-Hastings	$\lambda_{t,d} = \exp(\lambda_t + \lambda_d)$
$s(\cdot)$	Uniform$(0,1)$	Metropolis-Hastings	
α_B,α_L	Log Normal(.5,.5)	Metropolis-Hastings	$\alpha_L > \alpha_B$
ψ	Uniform density over $\mathbb{R}$	Metropolis-Hastings	$\gamma_t = \text{Logit}(G(t)'\psi)$
β	Standard Normal$(0,.1I)$	Gibbs	
η_k	Standard Normal$(0,.1I)$	Gibbs	
Σ_k	Inverse Wishart$(I,3)$	Gibbs	

Note: All parameters and estimation are route-specific.

Table 33: M-H Candidate Distribution Details

Parameter	Sampling Step	Candidate Dist.
λ	Metropolis-Hastings	Normal
$s(\cdot)$	Metropolis-Hastings	Normal
α_B,α_L	Metropolis-Hastings	Normal
$\gamma_t = \text{Logit}(G(t)'\psi)$	Metropolis-Hastings	Normal

Note: All parameters and estimation are route-specific.

D.3 Alternative Instrument Demand Results

We check the robustness to our demand results by considering additional instrument specifications. Here, we consider two alternative instruments. We reestimate demand for all 140 routes included in our estimation sample.

First, we estimate demand using solely the onward connecting traffic instrument. Second, we use solely the opportunity cost instrument. Tables summarizing the demand results, analogous to the presentation of the baseline specification in Table 2, appear in Table 34 and Table 35, respectively.

We find that our demand results are robust across instrument choice. Parameter estimates are similar across specifications, and average demand elasticities range between -1.1 to -1.2 across specifications. Figure 20 plots price coefficients and route-level elasticities across instrument specifications.

Table 34: Demand Estimates Summary: Onward-Connecting Traffic Instrument

		Mean	Std. Dev.	Median	25th Pct.	75th Pct.
Parameter						
Leis. Price Sens.	α_L	-1.543	0.743	-1.496	-1.986	-0.963
Bus. Price Sens.	α_B	-0.260	0.219	-0.206	-0.323	-0.119
DoW Prefs	Mon.	–	–	–	–	–
	Tues.	-0.056	0.210	-0.051	-0.166	0.075
	Wed.	-0.028	0.273	-0.012	-0.170	0.122
	Thurs.	-0.029	0.348	-0.023	-0.236	0.118
	Fri.	-0.131	0.332	-0.110	-0.264	0.079
	Sat.	-0.239	0.346	-0.229	-0.431	-0.071
	Sun.	-0.030	0.294	-0.011	-0.187	0.116
Week FE		Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y
Pr(Bus)	γ	0.392	0.198	0.362	0.254	0.489
Summary						
Percent. of 0s		91.401	3.614	92.137	90.124	94.225
Arrivals	A	1.744	1.403	1.163	0.788	2.373
Elas	e	-1.060	0.544	-0.962	-1.321	-0.696

Note: Parameter estimates for the 140 routes in the estimation sample. Statistics are calculated over routes, i.e., first the posterior mean of every parameter is calculated. Reported here are aspects of the posterior means across routes.

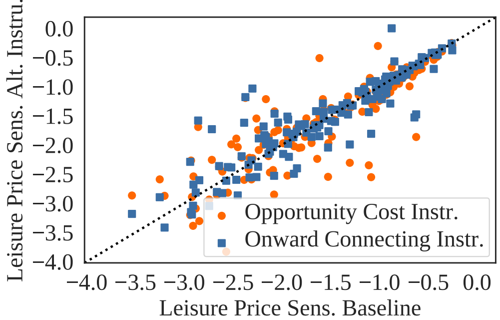
Table 35: Demand Estimates Summary: Opportunity Cost Instrument

		Mean	Std. Dev.	Median	25th Pct.	75th Pct.
Parameter						
Leis. Price Sens.	α_L	-1.580	0.766	-1.539	-2.045	-0.993
Bus. Price Sens.	α_B	-0.310	0.238	-0.248	-0.398	-0.157
DoW Prefs	Mon.	–	–	–	–	–
	Tues.	-0.066	0.233	-0.048	-0.186	0.068
	Wed.	-0.033	0.279	-0.014	-0.172	0.117
	Thurs.	-0.036	0.359	-0.031	-0.227	0.124
	Fri.	-0.129	0.340	-0.102	-0.266	0.090
	Sat.	-0.245	0.352	-0.250	-0.418	-0.066
	Sun.	-0.028	0.304	-0.008	-0.196	0.120
Week FE		Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y
Pr(Bus)	γ	0.370	0.187	0.332	0.228	0.455
Summary						
Percent. of 0s		91.401	3.614	92.137	90.124	94.225
Arrivals	A	1.766	1.399	1.172	0.810	2.408
Elas	e	-1.185	0.559	-1.066	-1.439	-0.830

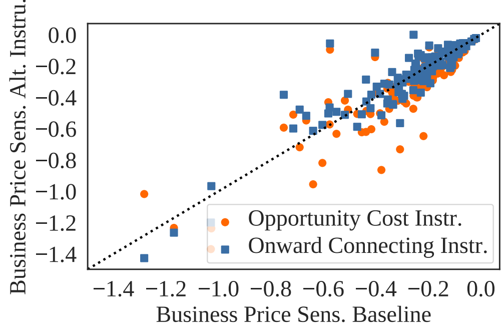
Note: Parameter estimates for the 140 routes in the estimation sample. Statistics are calculated over routes, i.e., first the posterior mean of every parameter is calculated. Reported here are aspects of the posterior means across routes.

Figure 20: Alternative Instrument Parameter Estimates

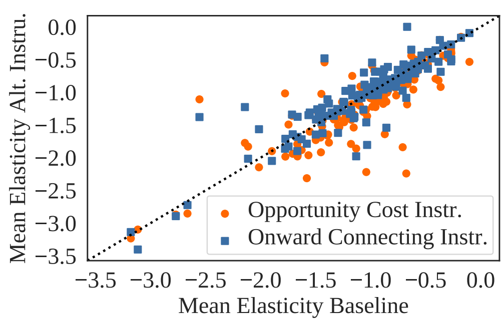
(a) Leisure Price Sensitivity



(b) Business Price Sensitivity



(c) Route-Level Elasticities



Each observation is a route-level posterior mean under alternative instrument sets. (a) Comparison of the leisure price sensitivity coefficients across instrument specifications. (b) Comparison of the business price sensitivity coefficients across instrument specifications. (c) Comparison of the mean route-level demand elasticity across instrument specifications.

D.4 The Impact of the Scaling Factor on Demand Estimates

We consider alternative specifications on our scaling factor ζ in order to understand how changes in imputed market size affect our demand estimates. We investigate two potential concerns: (i) that we are understating true arrivals if many individuals shop on travel websites, and (ii) our scaling factor may understate the presence of price-sensitive consumers who may primarily shop for tickets via online travel agencies early on. Therefore, we conduct three sets of robustness exercises. First, we multiple our arrival rates by an additional 50% within estimation and re-estimate demand for all 140 routes. Figure 36 shows a summary of our findings—parameter estimates are quantatively similar to our baseline estimates. Figure 21 compares price coefficients and demand elasticities.

Second, we multiply our estimated arrival rates by 1.5, 2, 2.5, ..., 5 within estimation for a single route. This is on top of the scaling factors included in estimation. Third, we repeat this exercise, but only consider the additional scaling for greater than 30 days before departure. Within 30 days before departure, we set this additional scaling factor equal to one, i.e., do not adjust it from our baseline arrival adjustment.

We apply the 16 robustness exercises to an example route ("Route 1"). This route's original demand elasticities are close to the average found across all routes, -1.2, compared to -1.1 across all routes. In Table 37, we provide demand estimates for the first set of demand robustness specifications. The first column denotes the route's baseline demand estimates. The following columns provide demand estimates under the additional scaling factors that are applied for all days before departure. Similarly, Table 38 provides demand estimates for "Route 1" for the additional eight demand specifications, where each column denotes the scaling factor that affects arrival rates early on (greater than 30 days before departure). The first column again repeats the original demand estimates.

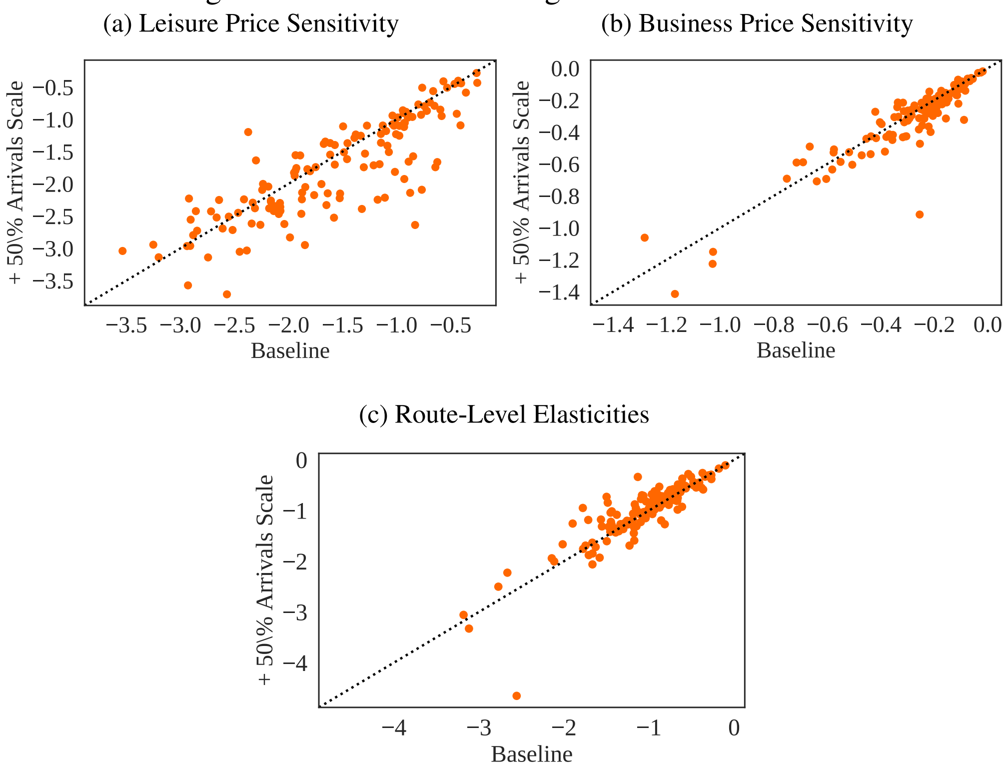
Across all sixteen additional specifications, we find that demand elasticities are stable, with averages between −1.2 and −1.0. Two specifications result in average demand elasticities closer to −0.9. These occur when market sizes are scaled up by over 350% compared to our original estimates. Critically, we confirm that under smaller additional scaling factors, such as 1.5×, where arrival rates are scaled up by an additional 50%, demand elasticities and estimated parameter values hardly change. The general pattern we find is that as the additional scaling factor increases, price sensitivities generally increase. For the scaling parameters that affect arrivals greater than 30 days before departure, there is a greater effect on the leisure consumer price sensitivity.

Table 36: Demand Estimates Summary: Additional Scaling 50%

		Mean	Std. Dev.	Median	25th Pct.	75th Pct.
Parameter						
Leis. Price Sens.	α_L	-1.750	0.773	-1.742	-2.358	-1.097
Bus. Price Sens.	α_B	-0.293	0.228	-0.244	-0.352	-0.145
DoW Prefs	Mon.	–	–	–	–	–
	Tues.	-0.052	0.196	-0.030	-0.175	0.045
	Wed.	-0.027	0.258	-0.018	-0.152	0.101
	Thurs.	-0.033	0.331	-0.031	-0.203	0.101
	Fri.	-0.119	0.318	-0.100	-0.254	0.070
	Sat.	-0.213	0.329	-0.220	-0.370	-0.057
	Sun.	-0.030	0.285	-0.013	-0.150	0.101
Week FE		Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y
Pr(Bus)	γ	0.412	0.197	0.377	0.280	0.511
Summary						
Percent. of 0s		91.401	3.614	92.137	90.124	94.225
Arrivals	A	2.636	2.093	1.745	1.212	3.593
Elas	e	-1.032	0.601	-0.925	-1.269	-0.678

Note: Parameter estimates for the 140 routes in the estimation sample. Statistics are calculated over routes, i.e., first the posterior mean of every parameter is calculated. Reported here are aspects of the posterior means across routes.

Figure 21: Additional Scaling Parameter Estimates



Each observation is a route-level posterior mean under an additional 50% scaling factor (a) Comparison of the leisure price sensitivity coefficients between baseline model and additional scaling. (b) Comparison of the business price sensitivity coefficients between baseline model and additional scaling. (c) Comparison of the mean route-level demand elasticity between baseline model and additional scaling.

Table 37: Demand Robustness: Alternative Scaling Factors for All Days Before Departure

Route		Baseline	1.5X	2.0X	2.5X	3.0X	3.5X	4.0X	4.5X	5.0X
Parameter										
Leis. Price Sens.	α_L	-1.038	-0.989	-1.193	-1.343	-1.563	-1.621	-1.794	-2.119	-1.976
		(0.068)	(0.115)	(0.063)	(0.068)	(0.066)	(0.072)	(0.152)	(0.100)	(0.147)
Bus. Price Sens.	α_B	-0.247	-0.246	-0.270	-0.299	-0.318	-0.352	-0.312	-0.370	-0.354
		(0.036)	(0.052)	(0.026)	(0.038)	(0.020)	(0.020)	(0.027)	(0.022)	(0.029)
DoW Prefs	Mon.	0.049	0.044	0.042	0.050	0.043	0.045	0.039	0.036	0.033
		(0.053)	(0.047)	(0.043)	(0.043)	(0.043)	(0.040)	(0.041)	(0.040)	(0.039)
	Tues.	0.009	0.013	0.021	0.022	0.024	0.005	0.027	0.019	0.010
		(0.054)	(0.047)	(0.050)	(0.049)	(0.044)	(0.040)	(0.046)	(0.038)	(0.042)
	Wed.	0.163	0.141	0.142	0.141	0.140	0.127	0.129	0.122	0.119
		(0.054)	(0.047)	(0.047)	(0.045)	(0.044)	(0.042)	(0.041)	(0.039)	(0.046)
	Thurs.	0.137	0.118	0.126	0.123	0.118	0.115	0.116	0.107	0.103
		(0.051)	(0.047)	(0.048)	(0.046)	(0.044)	(0.040)	(0.043)	(0.041)	(0.041)
	Fri.	0.148	0.134	0.132	0.138	0.122	0.119	0.105	0.106	0.105
		(0.050)	(0.045)	(0.043)	(0.044)	(0.042)	(0.038)	(0.041)	(0.040)	(0.037)
	Sat.	–	–	–	–	–	–	–	–	–
		–	–	–	–	–	–	–	–	–
	Sun.	0.065	0.059	0.064	0.067	0.063	0.065	0.056	0.061	0.063
		(0.051)	(0.047)	(0.047)	(0.045)	(0.042)	(0.038)	(0.042)	(0.039)	(0.040)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.217	0.224	0.307	0.307	0.344	0.338	0.382	0.366	0.391
Summary										
Percent. of 0s		85.321	85.321	85.321	85.321	85.321	85.321	85.321	85.321	85.321
First stage R^2		0.828	0.828	0.828	0.828	0.828	0.828	0.828	0.828	0.828
Arrivals	A	2.471	3.697	4.924	6.147	7.370	8.594	9.815	11.033	12.249
Emp. Q	Q	0.279	0.279	0.279	0.279	0.279	0.279	0.279	0.279	0.279
		(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.281	0.283	0.284	0.285	0.286	0.286	0.287	0.288	0.288
		(0.03,1.02)	(0.03,1.02)	(0.04,1.02)	(0.04,1.01)	(0.04,1.01)	(0.04,1.00)	(0.04,1.00)	(0.04,0.99)	(0.04,0.99)
Elas	e	-1.241	-1.211	-1.149	-1.034	-0.975	-0.931	-0.904	-1.006	-1.051
		(-2.07,-0.53)	(-2.03,-0.54)	(-1.84,-0.55)	(-1.47,-0.54)	(-1.20,-0.61)	(-1.16,-0.58)	(-1.04,-0.63)	(-1.16,-0.72)	(-1.24,-0.72)
Number of Flights		488	488	488	488	488	488	488	488	488
Number of Dep. Dates		393	393	393	393	393	393	393	393	393
Number of Obs.		58,076	58,076	58,076	58,076	58,076	58,076	58,076	58,076	58,076

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q", our model's prediction of the average total number of purchases is in "Model Q", and the estimated mean own-price elasticities are reported in the row labeled "Elas". We also report the 5th and 95th percentiles in parentheses. Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 38: Demand Robustness: Alternative Scaling Factors for ≥ 30 Days Before Departure

Route		Baseline	1.5X Early	2.0X Early	2.5X Early	3.0X Early	3.5X Early	4.0X Early	4.5X Early	5.0X Early
Parameter										
Leis. Price Sens.	α_L	-1.038	-1.197	-1.567	-1.795	-1.995	-2.070	-2.262	-2.409	-2.551
		(0.068)	(0.070)	(0.048)	(0.058)	(0.048)	(0.069)	(0.082)	(0.076)	(0.050)
Bus. Price Sens.	α_B	-0.247	-0.180	-0.182	-0.187	-0.213	-0.181	-0.183	-0.179	-0.186
		(0.036)	(0.030)	(0.022)	(0.022)	(0.032)	(0.017)	(0.040)	(0.025)	(0.022)
DoW Prefs	Mon.	0.049	0.059	0.063	0.069	0.078	0.071	0.074	0.073	0.077
		(0.053)	(0.053)	(0.049)	(0.046)	(0.049)	(0.044)	(0.045)	(0.045)	(0.045)
	Tues.	0.009	0.020	0.045	0.053	0.046	0.052	0.059	0.066	0.059
		(0.054)	(0.051)	(0.053)	(0.050)	(0.051)	(0.051)	(0.047)	(0.048)	(0.049)
	Wed.	0.163	0.164	0.176	0.179	0.177	0.180	0.182	0.187	0.178
		(0.054)	(0.051)	(0.052)	(0.050)	(0.053)	(0.052)	(0.045)	(0.050)	(0.048)
	Thurs.	0.137	0.132	0.141	0.146	0.144	0.145	0.146	0.144	0.148
		(0.051)	(0.052)	(0.047)	(0.048)	(0.051)	(0.047)	(0.048)	(0.046)	(0.046)
	Fri.	0.148	0.143	0.152	0.145	0.148	0.148	0.149	0.144	0.137
		(0.050)	(0.049)	(0.045)	(0.050)	(0.045)	(0.048)	(0.043)	(0.046)	(0.045)
	Sat.	–	–	–	–	–	–	–	–	–
		–	–	–	–	–	–	–	–	–
	Sun.	0.065	0.059	0.064	0.069	0.073	0.069	0.067	0.055	0.056
		(0.051)	(0.047)	(0.045)	(0.049)	(0.048)	(0.046)	(0.047)	(0.047)	(0.042)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.217	0.267	0.289	0.291	0.271	0.268	0.264	0.261	0.257
Summary										
Percent. of 0s		85.321	85.321	85.321	85.321	85.321	85.321	85.321	85.321	85.321
First stage R^2		0.828	0.828	0.828	0.828	0.828	0.828	0.828	0.828	0.828
Arrivals	A	2.471	3.083	3.692	4.298	4.902	5.505	6.104	6.705	7.307
Emp. Q	Q	0.279	0.279	0.279	0.279	0.279	0.279	0.279	0.279	0.279
		(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.281	0.282	0.282	0.283	0.283	0.283	0.283	0.283	0.282
		(0.03,1.02)	(0.03,1.01)	(0.04,1.00)	(0.04,1.00)	(0.04,0.99)	(0.04,0.98)	(0.04,0.98)	(0.04,0.98)	(0.04,0.97)
Elas	e	-1.241	-1.281	-1.149	-1.100	-1.135	-1.094	-1.023	-0.960	-0.974
		(-2.07,-0.53)	(-2.13,-0.39)	(-1.60,-0.32)	(-1.52,-0.32)	(-1.60,-0.34)	(-1.60,-0.36)	(-1.58,-0.30)	(-1.51,-0.29)	(-1.55,-0.35)
Number of Flights		488	488	488	488	488	488	488	488	488
Number of Dep. Dates		393	393	393	393	393	393	393	393	393
Number of Obs.		58,076	58,076	58,076	58,076	58,076	58,076	58,076	58,076	58,076

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q", our model's prediction of the average total number of purchases is in "Model Q", and the estimated mean own-price elasticities are reported in the row labeled "Elas". We also report the 5th and 95th percentiles in parentheses. Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

D.5 Demand Estimates Imposing Supply-Side Conditions

Table 39 compares demand estimates assuming observed prices are the result of the firm solving a dynamic programming program as a single entity. We use the model of Williams (2022) for demonstration purposes. The dynamic program is given by

$$\begin{aligned}V_t(C_t,\omega_t) = \max_{p\in \text{Fares}(t)} \bigg(& p_t \cdot \mathbb{E}_t\left[q_t(p_t;C_t)\right] + \omega_{tp} \\ & + \int_{\omega_{t+1},C_{t+1}\,|\,\omega_t,p,C_t,} V_{t+1}(C_{t+1},\omega_{t+1}) dH_t(\omega_{t+1},C_{t+1}\,|\,\omega_t,p,C_t)\bigg),\end{aligned}$$

where $V_t(C_t,\omega_t)$ is the value function given the state (t,C_t,ω_t), $\omega_t \in \mathbb{R}^{A(t)}$ are assumed to be IID Type-1 Extreme Value (T1EV) unobservables, with scale parameter $\sigma > 0$, Fares(t) are the pricing department's fare decisions for period t, $\mathbb{E}_t\left[q_t(p_t;C_t)\right]$ is expected demand. We assume conditional independence is satisfied and therefore, $h_t(\omega_{t+1},C_{t+1}\,|\,\omega_t,p_t,C_t) = g(\omega_{t+1})f_t(C_{t+1}\,|\,p_t,C_t)$. The capacity transitions $f_t(\cdot)$ are also based on the censored Poisson distributions of demand and are equal to $C_{t+1} = C_t - \min\left\{\tilde{q}_t, C_t\right\}$, where $\tilde{q}_t$ is the realized demand draw. The firm faces two boundary conditions: (i) unsold seats are scrapped and (ii) it cannot sell any additional seats if $C_t = 0$. For this route, almost all departures have a single flight per day. When there is more than one flight a day, we assume they are priced independently. Finally, we use $\lambda^B_{t,d,r}$ and $\tilde{\lambda}^L_{t,d,r}$ as inputs and therefore, do not re-estimate these parameters.

With these assumptions, the conditional value function is equal to

$$\begin{aligned}EV_t(p_t,C_t) = \int_{C_{t+1}} & \left[\sigma \ln\left(\sum_{p_{t+1}\in \text{Fares}(t)} \exp\left(\frac{p_{t+1}\cdot \mathbb{E}_{t+1}\left[q_{t+1}(p_{t+1};C_{t+1})\right] + EV_{t+1}(p_{t+1},C_{t+1})}{\sigma}\right)\right)\right] \\ & \times f_t(C_{t+1}|C_t,p_t) + \sigma\phi,\end{aligned}$$

where ϕ is Euler's constant. The probability the firm chooses price p_t is equal to

$$CCP_t(p_t\,;\,C_t) = \frac{\exp\left\{\left(p_t \cdot \mathbb{E}_t\left[q_t(p_t; C_t)\right] + EV_t(p_t, C_t)\right)/\sigma\right\}}{\sum_{p'_t \in \text{Fares}(t)} \exp\left\{\left(p'_t \cdot \mathbb{E}_t\left[q_t(p'_t; C_t)\right] + EV_t(p'_t, C_t)\right)/\sigma\right\}}.$$

Finally, this allows us to obtain the following log-likelihood for the sample

$$\max_{\alpha,\beta,\sigma} \sum_F \sum_T \log\left(CCP_t(p_t\,;\,C_t)\right) + \log\left(f_t(C_{t+1}|C_t, p_t)\right).$$

Table 39: Demand Estimates for Route 1

		Posterior Mean	Std. Error	Point Estimate	Std. Error
Parameter					
Leis. Price Sens.	α_L	-1.038	0.068	-0.997	0.009
Bus. Price Sens.	α_B	-0.247	0.036	-0.473	0.011
DoW Prefs	Mon.	0.049	0.053	0.215	0.033
	Tues.	0.009	0.054	0.177	0.042
	Wed.	0.163	0.054	0.275	0.057
	Thurs.	0.137	0.051	0.130	0.084
	Fri.	0.148	0.050	0.211	0.143
	Sat.	–	–	–	–
	Sun.	0.065	0.051	0.075	0.034
Week FE		Y		N	
ToD FE		Y		N	
Pr(Bus)	γ	0.217		0.199	
Summary					
Percent. of 0s		85.31		85.31	
Arrivals	A	2.471		2.494	
Elas	e	-1.241		-5.076	

Note: Comparison of our demand estimates to a model that imposes supply side conditions in estimation (Williams, 2022). We estimate $\sigma = 0.09$.

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Table 40: Demand Results Summary Table: Opportunity Cost Instrument

Route		1	2	3	4	5	6	7	8	9	10
Parameter											
Leis. Price Sens.	α_L	-1.086	-1.215	-0.418	-0.574	-1.868	-1.193	-2.872	-1.312	-1.891	-2.022
		(0.073)	(0.150)	(0.018)	(0.026)	(0.126)	(0.124)	(0.170)	(0.093)	(0.088)	(0.224)
Bus. Price Sens.	α_B	-0.320	-0.603	-0.040	-0.182	-0.126	-0.326	-1.017	-0.098	-0.506	-0.304
		(0.055)	(0.101)	(0.007)	(0.019)	(0.020)	(0.044)	(0.187)	(0.025)	(0.069)	(0.085)
DoW Prefs	Mon.	0.054	-0.012	-0.189	-0.520	0.097	–	–	0.249	0.336	0.529
		(0.055)	(0.090)	(0.053)	(0.090)	(0.066)	–	–	(0.081)	(0.063)	(0.142)
	Tues.	-0.010	0.140	0.200	-0.426	-0.126	-0.132	-0.056	0.087	0.333	0.303
		(0.058)	(0.064)	(0.057)	(0.092)	(0.069)	(0.067)	(0.066)	(0.099)	(0.086)	(0.139)
	Wed.	0.139	0.138	0.290	-0.122	-0.095	-0.072	-0.077	–	0.272	0.531
		(0.061)	(0.054)	(0.051)	(0.094)	(0.063)	(0.073)	(0.075)	–	(0.075)	(0.162)
	Thurs.	0.131	0.067	0.314	-0.034	-0.165	-0.073	-0.097	-0.152	0.366	0.206
		(0.055)	(0.061)	(0.051)	(0.089)	(0.072)	(0.069)	(0.087)	(0.085)	(0.057)	(0.128)
	Fri.	0.161	0.074	0.186	–	–	-0.149	-0.280	-0.016	0.241	0.134
		(0.053)	(0.067)	(0.054)	–	–	(0.072)	(0.081)	(0.089)	(0.057)	(0.099)
	Sat.	–	-0.074	-0.035	0.014	-0.133	-0.112	-0.045	-0.289	-0.181	–
		–	(0.055)	(0.052)	(0.086)	(0.069)	(0.069)	(0.092)	(0.094)	(0.098)	–
	Sun.	0.081	–	–	-0.146	0.015	0.312	-0.011	-0.002	–	0.151
		(0.052)	–	–	(0.086)	(0.068)	(0.076)	(0.094)	(0.084)	–	(0.131)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.187	0.213	0.264	0.162	0.697	0.668	0.213	0.321	0.358	0.326
Summary											
Percent. of 0s		85.321	94.538	88.235	85.724	94.010	92.034	95.437	92.521	94.821	95.691
First stage R^2		0.828	0.690	0.614	0.730	0.820	0.771	0.868	0.777	0.655	0.587
Arrivals	A	2.470	1.017	1.894	3.570	3.912	2.920	0.617	0.703	0.893	0.358
Emp. Q	Q	0.279	0.226	0.228	0.249	0.195	0.172	0.095	0.192	0.243	0.104
		(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)
Model Q	$E[Q]$	0.281	0.230	0.229	0.253	0.210	0.178	0.096	0.188	0.243	0.103
		(0.03,1.02)	(0.03,0.79)	(0.04,0.71)	(0.07,0.79)	(0.04,0.64)	(0.03,0.54)	(0.01,0.39)	(0.02,0.67)	(0.02,0.88)	(0.01,0.35)
Elas	e	-1.458	-1.641	-0.833	-1.983	-0.479	-0.875	-1.494	-1.015	-1.343	-1.419
		(-2.47,-0.67)	(-2.61,-0.98)	(-1.37,-0.26)	(-2.97,-1.02)	(-0.74,-0.34)	(-1.24,-0.70)	(-1.86,-0.67)	(-1.47,-0.23)	(-1.70,-0.74)	(-2.08,-0.54)
Number of Flights		488	1,290	509	107	331	315	670	752	1,060	487
Number of Dep. Dates		393	379	393	107	163	203	392	387	274	238
Number of Obs.		58,076	156,777	60,721	12,791	38,847	37,319	79,955	89,486	124,843	56,307

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 41: Demand Results Summary Table: Opportunity Cost Instrument

Route		11	12	13	14	15	16	17	18	19	20
Parameter											
Leis. Price Sens.	α_L	-2.866	-0.694	-0.834	-0.407	-1.911	-1.602	-1.423	-2.539	-1.990	-1.138
		(0.290)	(0.139)	(0.070)	(0.036)	(0.139)	(0.106)	(0.209)	(0.170)	(0.088)	(0.079)
Bus. Price Sens.	α_B	-0.143	-0.421	-0.210	-0.096	-0.399	-0.404	-0.099	-0.510	-0.081	-0.158
		(0.035)	(0.105)	(0.034)	(0.017)	(0.048)	(0.040)	(0.022)	(0.109)	(0.014)	(0.036)
DoW Prefs	Mon.	0.152	0.476	0.140	0.173	–	–	–	0.287	0.225	–
		(0.055)	(0.129)	(0.121)	(0.057)	–	–	–	(0.084)	(0.034)	–
	Tues.	0.272	-0.099	0.081	-0.042	-0.251	0.059	-0.072	0.242	0.213	-0.138
		(0.063)	(0.071)	(0.134)	(0.056)	(0.100)	(0.095)	(0.068)	(0.080)	(0.037)	(0.085)
	Wed.	0.133	0.064	-0.011	-0.043	-0.366	-0.014	-0.203	0.128	0.135	-0.169
		(0.058)	(0.075)	(0.131)	(0.060)	(0.095)	(0.080)	(0.062)	(0.079)	(0.032)	(0.082)
	Thurs.	0.045	–	-0.167	-0.018	-0.310	-0.003	-0.234	–	–	-0.245
		(0.048)	–	(0.125)	(0.058)	(0.090)	(0.070)	(0.064)	–	–	(0.077)
	Fri.	–	0.042	–	–	-0.338	-0.048	-0.355	-0.096	-0.146	-0.362
		–	(0.075)	–	–	(0.086)	(0.074)	(0.059)	(0.070)	(0.031)	(0.075)
	Sat.	-0.168	0.509	-0.065	-0.232	-0.256	-0.434	-0.341	-0.078	-0.123	-0.334
		(0.064)	(0.142)	(0.110)	(0.061)	(0.086)	(0.068)	(0.070)	(0.092)	(0.035)	(0.081)
	Sun.	-0.080	1.065	0.053	0.157	-0.445	-0.300	-0.278	0.469	-0.242	-0.271
		(0.048)	(0.206)	(0.108)	(0.053)	(0.079)	(0.074)	(0.064)	(0.105)	(0.029)	(0.076)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.543	0.188	0.171	0.262	0.335	0.266	0.394	0.219	0.461	0.485
Summary											
Percent. of 0s		90.947	84.530	94.297	88.374	90.659	91.792	90.133	93.015	86.994	91.174
First stage R^2		0.849	0.760	0.798	0.649	0.798	0.653	0.617	0.611	0.827	0.601
Arrivals	A	1.812	3.020	2.461	2.185	0.848	0.891	1.111	1.007	5.722	0.984
Emp. Q	Q	0.571	0.288	0.099	0.225	0.128	0.302	0.249	0.097	1.195	0.118
		(0.00,3.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,6.00)	(0.00,1.00)
Model Q	$E[Q]$	0.571	0.288	0.106	0.226	0.128	0.298	0.247	0.097	1.199	0.118
		(0.05,2.13)	(0.08,0.99)	(0.02,0.28)	(0.04,0.72)	(0.01,0.46)	(0.02,1.05)	(0.02,0.86)	(0.01,0.35)	(0.11,4.25)	(0.02,0.34)
Elas	e	-0.425	-1.963	-1.731	-0.762	-1.300	-1.793	-0.670	-1.321	-0.441	-0.682
		(-0.64,-0.17)	(-3.52,-0.90)	(-2.70,-0.94)	(-1.34,-0.35)	(-2.07,-0.46)	(-2.73,-0.65)	(-1.11,-0.17)	(-2.09,-0.51)	(-0.71,-0.17)	(-1.20,-0.27)
Number of Flights		1,453	217	123	444	304	960	647	335	1,712	391
Number of Dep. Dates		315	217	103	372	304	343	351	335	285	371
Number of Obs.		170,795	25,825	13,448	52,716	35,746	110,780	76,854	40,059	200,018	44,405

Note: For the “parameter” rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the “summary” rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled “Percent. of 0s”, the r-squared of a regression of prices on the controls and instruments is in “First stage R^2”, the mean of the estimated posterior distribution for the arrivals process is in “A”, the average total number of purchases observed in the data is in “Emp. Q” with the 5th and 95th percentile of purchases in parentheses, our model’s prediction of the average total number of purchases is in “Model Q” with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled “Elas”. Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 42: Demand Results Summary Table: Opportunity Cost Instrument

Route		21	22	23	24	25	26	27	28	29	30
Parameter											
Leis. Price Sens.	α_L	-1.544	-0.511	-3.386	-1.001	-2.373	-1.083	-1.744	-0.741	-0.970	-1.968
		(0.062)	(0.268)	(0.148)	(0.062)	(0.086)	(0.083)	(0.056)	(0.055)	(0.102)	(0.086)
Bus. Price Sens.	α_B	-0.207	-0.024	-1.369	-0.115	-0.478	-0.179	-0.287	-0.168	-0.173	-0.073
		(0.031)	(0.005)	(0.155)	(0.022)	(0.023)	(0.033)	(0.055)	(0.022)	(0.032)	(0.019)
DoW Prefs	Mon.	0.239	–	-0.136	–	0.612	-0.223	–	0.092	-0.049	0.138
		(0.097)	–	(0.083)	–	(0.095)	(0.082)	–	(0.058)	(0.061)	(0.047)
	Tues.	-0.102	-0.174	–	-0.188	0.517	-0.255	-0.044	-0.093	-0.127	0.023
		(0.112)	(0.057)	–	(0.086)	(0.086)	(0.089)	(0.067)	(0.063)	(0.075)	(0.050)
	Wed.	-0.051	-0.277	0.090	-0.240	0.267	-0.134	0.078	-0.074	-0.014	0.135
		(0.104)	(0.053)	(0.088)	(0.094)	(0.085)	(0.087)	(0.059)	(0.059)	(0.065)	(0.052)
	Thurs.	0.079	-0.342	-0.107	-0.429	0.013	–	-0.123	-0.044	-0.037	0.086
		(0.101)	(0.055)	(0.088)	(0.083)	(0.081)	–	(0.071)	(0.052)	(0.055)	(0.050)
	Fri.	–	-0.422	-0.077	-0.311	-0.047	-0.134	-0.374	–	-0.148	–
		–	(0.056)	(0.077)	(0.079)	(0.087)	(0.087)	(0.053)	–	(0.056)	–
	Sat.	0.080	-0.397	0.188	-0.569	–	-0.277	-0.365	-0.086	-0.073	-0.376
		(0.130)	(0.062)	(0.090)	(0.081)	–	(0.081)	(0.048)	(0.056)	(0.058)	(0.053)
	Sun.	-0.047	0.022	0.592	-0.004	0.364	0.286	-0.054	0.345	–	-0.058
		(0.104)	(0.055)	(0.090)	(0.070)	(0.067)	(0.084)	(0.069)	(0.063)	–	(0.056)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.293	0.447	0.152	0.227	0.457	0.335	0.444	0.328	0.348	0.754
Summary											
Percent. of 0s		90.351	88.639	95.504	92.245	94.838	90.928	92.930	90.275	92.919	92.532
First stage R^2		0.691	0.632	0.880	0.780	0.705	0.612	0.728	0.748	0.781	0.844
Arrivals	A	0.599	1.857	0.572	0.682	0.925	0.969	1.805	1.614	1.551	1.870
Emp. Q	Q	0.134	0.222	0.093	0.198	0.242	0.120	0.549	0.315	0.307	0.332
		(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,3.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.132	0.221	0.094	0.194	0.243	0.119	0.551	0.317	0.310	0.337
		(0.01,0.51)	(0.04,0.66)	(0.01,0.38)	(0.02,0.68)	(0.02,0.86)	(0.02,0.35)	(0.04,2.17)	(0.04,0.93)	(0.05,0.91)	(0.05,1.01)
Elas	e	-1.415	-0.536	-1.883	-1.300	-1.182	-1.086	-0.959	-0.935	-0.934	-0.199
		(-2.36,-0.27)	(-0.87,-0.15)	(-2.21,-0.95)	(-2.23,-0.22)	(-1.48,-0.74)	(-1.77,-0.48)	(-1.32,-0.48)	(-1.54,-0.37)	(-1.38,-0.38)	(-0.28,-0.13)
Number of Flights		259	517	671	752	1,152	364	1,660	792	983	1,004
Number of Dep. Dates		258	394	393	387	298	347	279	322	307	308
Number of Obs.		30,531	61,710	80,066	89,341	135,404	41,459	195,980	91,287	116,084	118,320

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 43: Demand Results Summary Table: Opportunity Cost Instrument

Route		31	32	33	34	35	36	37	38	39	40
Parameter											
Leis. Price Sens.	α_L	-2.037	-0.874	-0.715	-1.038	-1.830	-1.757	-2.856	-0.902	-2.220	-1.406
		(0.114)	(0.087)	(0.037)	(0.033)	(0.101)	(0.131)	(0.058)	(0.085)	(0.046)	(0.079)
Bus. Price Sens.	α_B	-0.280	-0.215	-0.192	-0.033	-0.233	-0.097	-0.431	-0.228	-0.288	-0.573
		(0.052)	(0.047)	(0.032)	(0.007)	(0.041)	(0.020)	(0.102)	(0.048)	(0.033)	(0.038)
DoW Prefs	Mon.	0.281	–	-0.044	-0.120	–	0.003	0.179	0.101	–	-0.101
		(0.143)	–	(0.056)	(0.051)	–	(0.068)	(0.107)	(0.065)	–	(0.072)
	Tues.	-0.031	-0.231	-0.252	-0.185	-0.212	–	0.187	-0.066	-0.020	-0.002
		(0.091)	(0.073)	(0.063)	(0.052)	(0.080)	–	(0.111)	(0.060)	(0.100)	(0.090)
	Wed.	–	-0.366	-0.184	–	-0.254	-0.008	–	–	0.006	0.100
		–	(0.065)	(0.071)	–	(0.093)	(0.070)	–	–	(0.095)	(0.078)
	Thurs.	-0.179	-0.271	-0.182	0.083	-0.466	0.001	-0.177	-0.061	-0.067	0.021
		(0.102)	(0.065)	(0.060)	(0.050)	(0.076)	(0.067)	(0.092)	(0.055)	(0.069)	(0.073)
	Fri.	-0.657	-0.379	-0.232	0.193	-0.397	-0.015	-0.066	-0.089	-0.181	–
		(0.077)	(0.059)	(0.058)	(0.051)	(0.090)	(0.062)	(0.126)	(0.056)	(0.066)	–
	Sat.	-0.546	-0.486	-0.271	0.828	-0.647	-0.079	-0.177	-0.217	-0.527	-0.105
		(0.101)	(0.063)	(0.065)	(0.062)	(0.102)	(0.069)	(0.108)	(0.059)	(0.081)	(0.078)
	Sun.	-0.137	0.040	–	0.341	0.020	0.132	0.256	0.207	-0.095	0.140
		(0.092)	(0.062)	–	(0.053)	(0.089)	(0.065)	(0.105)	(0.065)	(0.073)	(0.086)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.514	0.259	0.357	0.015	0.450	0.584	0.217	0.409	0.435	0.239
Summary											
Percent. of 0s		94.349	92.138	91.084	86.460	94.456	91.752	95.727	90.556	93.991	92.280
First stage R^2		0.682	0.721	0.746	0.654	0.739	0.740	0.736	0.764	0.720	0.846
Arrivals	A	0.682	1.160	1.174	6.800	0.602	1.518	0.276	1.789	0.996	1.050
Emp. Q	Q	0.194	0.282	0.225	0.300	0.181	0.255	0.101	0.255	0.250	0.232
		(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.194	0.282	0.225	0.320	0.180	0.256	0.100	0.257	0.252	0.231
		(0.01,0.69)	(0.04,0.86)	(0.03,0.68)	(0.07,1.16)	(0.02,0.62)	(0.04,0.75)	(0.00,0.47)	(0.04,0.72)	(0.03,0.79)	(0.02,0.83)
Elas	e	-0.407	-1.149	-0.939	-3.234	-0.891	-0.442	-1.830	-1.025	-0.957	-1.602
		(-0.56,-0.27)	(-1.89,-0.48)	(-1.61,-0.32)	(-5.18,-1.03)	(-1.30,-0.44)	(-0.75,-0.17)	(-2.89,-0.36)	(-1.63,-0.42)	(-1.30,-0.62)	(-2.80,-0.63)
Number of Flights		807	836	713	394	941	729	721	772	952	516
Number of Dep. Dates		276	309	373	389	354	311	365	386	279	221
Number of Obs.		95,441	98,207	84,575	47,069	111,049	85,158	85,695	91,643	110,327	58,546

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 44: Demand Results Summary Table: Opportunity Cost Instrument

Route		41	42	43	44	45	46	47	48	49	50
Parameter											
Leis. Price Sens.	α_L	-0.912	-2.590	-0.831	-1.853	-1.726	-0.397	-0.851	-1.692	-3.830	-1.698
		(0.030)	(0.096)	(0.036)	(0.076)	(0.064)	(0.103)	(0.049)	(0.059)	(0.423)	(0.042)
Bus. Price Sens.	α_B	-0.186	-0.154	-0.111	-0.225	-0.143	-0.247	-0.103	-0.095	-0.119	-0.067
		(0.030)	(0.015)	(0.019)	(0.086)	(0.020)	(0.072)	(0.018)	(0.019)	(0.035)	(0.013)
DoW Prefs	Mon.	0.257	0.030	-0.057	0.070	0.179	-0.144	-0.111	-0.032	-0.106	1.957
		(0.078)	(0.055)	(0.053)	(0.049)	(0.062)	(0.077)	(0.073)	(0.034)	(0.089)	(0.134)
	Tues.	0.029	0.226	-0.118	0.198	0.266	-0.393	-0.144	0.103	–	0.531
		(0.079)	(0.043)	(0.058)	(0.053)	(0.064)	(0.080)	(0.076)	(0.037)	–	(0.092)
	Wed.	0.152	0.145	-0.041	0.227	0.257	-0.248	0.018	0.229	0.222	0.171
		(0.079)	(0.050)	(0.056)	(0.057)	(0.054)	(0.074)	(0.085)	(0.044)	(0.128)	(0.086)
	Thurs.	-0.020	0.070	0.039	0.089	0.133	0.038	0.097	0.229	0.143	-0.042
		(0.076)	(0.052)	(0.056)	(0.050)	(0.064)	(0.063)	(0.069)	(0.038)	(0.104)	(0.085)
	Fri.	–	-0.205	-0.034	-0.083	0.150	–	-0.058	-0.035	-0.282	–
		–	(0.059)	(0.049)	(0.054)	(0.048)	–	(0.073)	(0.029)	(0.094)	–
	Sat.	-0.184	-0.266	-0.144	-0.209	–	0.101	–	-0.087	-0.574	-0.212
		(0.075)	(0.061)	(0.051)	(0.050)	–	(0.073)	–	(0.035)	(0.092)	(0.129)
	Sun.	0.402	–	–	–	0.191	-0.191	0.016	–	-0.294	-0.219
		(0.075)	–	–	–	(0.065)	(0.064)	(0.072)	–	(0.123)	(0.089)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.279	0.520	0.266	0.440	0.443	0.494	0.291	0.448	0.550	0.320
Summary											
Percent. of 0s		88.584	92.883	90.439	92.235	90.800	84.262	90.305	86.333	90.623	83.368
First stage R^2		0.775	0.741	0.793	0.735	0.853	0.733	0.630	0.786	0.776	0.800
Arrivals	A	0.900	1.812	1.592	2.222	1.859	3.562	1.061	5.634	0.789	0.983
Emp. Q	Q	0.170	0.553	0.302	0.419	0.578	0.310	0.244	1.238	0.330	0.316
		(0.00,1.00)	(0.00,3.00)	(0.00,2.00)	(0.00,2.00)	(0.00,3.00)	(0.00,2.00)	(0.00,2.00)	(0.00,6.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.165	0.551	0.303	0.422	0.580	0.310	0.242	1.242	0.326	0.290
		(0.02,0.56)	(0.03,2.16)	(0.04,0.89)	(0.04,1.43)	(0.04,2.23)	(0.08,1.10)	(0.02,0.85)	(0.12,4.39)	(0.01,1.42)	(0.02,1.17)
Elas	e	-0.988	-0.405	-0.981	-0.919	-0.591	-0.940	-0.633	-0.543	-0.435	-1.301
		(-1.92,-0.24)	(-0.72,-0.19)	(-1.73,-0.27)	(-1.25,-0.43)	(-0.82,-0.23)	(-1.42,-0.45)	(-1.26,-0.17)	(-0.78,-0.20)	(-0.80,-0.14)	(-3.05,-0.13)
Number of Flights		390	1,641	876	1,462	1,387	221	659	1,703	559	333
Number of Dep. Dates		390	276	375	359	301	221	355	284	214	333
Number of Obs.		46,582	194,693	103,754	173,340	162,964	26,363	77,914	204,289	66,438	39,701

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 45: Demand Results Summary Table: Opportunity Cost Instrument

Route		51	52	53	54	55	56	57	58	59
Parameter										
Leis. Price Sens.	α_L	-3.305	-2.226	-0.253	-0.574	-2.238	-0.627	-1.635	-1.892	-1.997
		(0.201)	(0.233)	(0.019)	(0.052)	(0.120)	(0.051)	(0.079)	(0.119)	(0.030)
Bus. Price Sens.	α_B	-0.427	-0.272	-0.086	-0.179	-0.238	-0.263	-0.272	-0.300	-0.819
		(0.033)	(0.032)	(0.013)	(0.033)	(0.044)	(0.033)	(0.055)	(0.045)	(0.043)
DoW Prefs	Mon.	-0.301	0.012	-0.231	-0.026	–	0.106	0.310	0.214	0.359
		(0.100)	(0.116)	(0.045)	(0.087)	–	(0.111)	(0.094)	(0.115)	(0.083)
	Tues.	–	-0.110	-0.166	0.187	-0.009	-0.020	0.041	-0.073	0.473
		–	(0.119)	(0.045)	(0.094)	(0.069)	(0.105)	(0.101)	(0.114)	(0.088)
	Wed.	0.283	0.080	-0.187	0.118	0.048	0.223	-0.075	–	0.388
		(0.099)	(0.110)	(0.045)	(0.092)	(0.058)	(0.102)	(0.093)	–	(0.091)
	Thurs.	0.039	-0.040	-0.136	0.052	0.231	0.275	–	0.131	0.217
		(0.143)	(0.117)	(0.044)	(0.086)	(0.070)	(0.095)	–	(0.115)	(0.081)
	Fri.	-0.110	-0.155	-0.033	–	0.084	0.142	-0.315	-0.003	–
		(0.158)	(0.110)	(0.041)	–	(0.076)	(0.100)	(0.083)	(0.114)	–
	Sat.	-0.355	-0.135	–	-0.020	0.074	0.016	-0.335	-0.055	-0.081
		(0.119)	(0.093)	–	(0.087)	(0.071)	(0.086)	(0.093)	(0.134)	(0.073)
	Sun.	-0.502	–	-0.052	0.353	0.067	–	0.386	0.481	0.218
		(0.105)	–	(0.042)	(0.086)	(0.071)	–	(0.085)	(0.117)	(0.069)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.441	0.752	0.292	0.142	0.661	0.416	0.366	0.355	0.208
Summary										
Percent. of 0s		95.353	93.047	81.276	85.095	93.798	93.640	89.817	89.906	95.291
First stage R^2		0.751	0.809	0.669	0.569	0.763	0.763	0.794	0.740	0.708
Arrivals	A	0.595	3.127	6.387	3.884	4.804	2.706	0.837	0.578	0.654
Emp. Q	Q	0.164	0.115	0.369	0.262	0.193	0.115	0.143	0.142	0.166
		(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)
Model Q	$E[Q]$	0.166	0.121	0.379	0.266	0.210	0.122	0.142	0.140	0.167
		(0.01,0.71)	(0.02,0.31)	(0.13,1.27)	(0.07,0.84)	(0.04,0.66)	(0.03,0.32)	(0.01,0.51)	(0.01,0.55)	(0.01,0.71)
Elas	e	-1.840	-0.891	-0.840	-1.860	-0.819	-1.226	-1.083	-1.431	-2.314
		(-2.38,-1.03)	(-1.37,-0.56)	(-1.27,-0.54)	(-2.58,-0.94)	(-1.24,-0.59)	(-2.03,-0.74)	(-1.92,-0.29)	(-2.43,-0.38)	(-3.22,-1.30)
Number of Flights		854	96	396	107	374	145	311	260	927
Number of Dep. Dates		291	96	396	107	194	117	311	260	317
Number of Obs.		100,922	11,463	47,336	12,774	44,311	15,440	36,570	30,454	109,772

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 46: Demand Results Summary Table: Opportunity Cost Instrument

Route		60	61	62	63	64	65	66	67	68
Parameter										
Leis. Price Sens.	α_L	-0.667	-1.214	-1.855	-1.220	-1.368	-1.971	-2.472	-2.306	-0.764
		(0.119)	(0.249)	(0.029)	(0.091)	(0.055)	(0.086)	(0.091)	(0.045)	(0.149)
Bus. Price Sens.	α_B	-0.389	-0.487	-0.593	-0.305	-0.248	-0.502	-0.370	-0.647	-0.269
		(0.042)	(0.054)	(0.030)	(0.062)	(0.029)	(0.070)	(0.062)	(0.061)	(0.031)
DoW Prefs	Mon.	–	-0.361	0.168	–	-0.176	0.544	-0.058	0.899	-0.340
		–	(0.174)	(0.083)	–	(0.112)	(0.120)	(0.140)	(0.132)	(0.080)
	Tues.	-0.194	-0.685	0.219	-0.108	-0.302	0.387	–	0.663	-0.321
		(0.112)	(0.165)	(0.070)	(0.100)	(0.127)	(0.106)	–	(0.153)	(0.082)
	Wed.	0.241	–	0.121	0.072	–	0.501	-0.174	0.652	–
		(0.105)	–	(0.081)	(0.097)	–	(0.100)	(0.121)	(0.113)	–
	Thurs.	-0.027	0.101	-0.192	0.079	0.420	0.194	-0.352	0.129	0.001
		(0.107)	(0.158)	(0.083)	(0.094)	(0.109)	(0.135)	(0.131)	(0.119)	(0.075)
	Fri.	0.107	-0.151	-0.708	-0.199	0.145	–	-0.725	-0.060	-0.158
		(0.106)	(0.156)	(0.079)	(0.086)	(0.087)	–	(0.095)	(0.110)	(0.079)
	Sat.	0.024	-0.097	-0.627	-0.300	0.009	-0.268	-0.445	–	-0.288
		(0.106)	(0.125)	(0.074)	(0.099)	(0.117)	(0.115)	(0.116)	–	(0.082)
	Sun.	-0.196	-0.366	–	0.419	-0.101	0.306	0.141	0.690	-0.121
		(0.101)	(0.133)	–	(0.100)	(0.118)	(0.112)	(0.148)	(0.144)	(0.079)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.520	0.873	0.278	0.238	0.505	0.457	0.328	0.324	0.662
Summary										
Percent. of 0s		93.403	93.125	92.490	90.095	96.403	96.128	96.326	94.233	93.029
First stage R^2		0.726	0.686	0.703	0.799	0.736	0.700	0.623	0.695	0.780
Arrivals	A	3.060	4.622	1.226	0.876	0.388	0.337	0.253	0.884	3.508
Emp. Q	Q	0.117	0.142	0.474	0.136	0.230	0.130	0.096	0.340	0.119
		(0.00,1.00)	(0.00,1.00)	(0.00,3.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)
Model Q	$E[Q]$	0.124	0.154	0.468	0.136	0.224	0.129	0.096	0.334	0.126
		(0.02,0.34)	(0.03,0.38)	(0.02,2.09)	(0.01,0.49)	(0.00,1.05)	(0.00,0.63)	(0.00,0.49)	(0.02,1.40)	(0.03,0.32)
Elas	e	-1.186	-1.646	-1.774	-1.148	-1.003	-0.988	-1.358	-1.770	-0.864
		(-1.73,-0.82)	(-3.27,-1.03)	(-2.57,-0.88)	(-2.03,-0.48)	(-2.41,-0.26)	(-1.41,-0.58)	(-2.11,-0.58)	(-2.67,-0.71)	(-1.32,-0.51)
Number of Flights		117	53	1,120	283	709	965	671	602	211
Number of Dep. Dates		117	53	236	277	131	351	302	133	205
Number of Obs.		13,960	6,342	129,887	32,711	83,245	114,462	79,617	70,103	25,005

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 47: Demand Results Summary Table: Opportunity Cost Instrument

Route		69	70	71	72	73	74	75	76	77
Parameter										
Leis. Price Sens.	α_L	-1.090	-1.197	-1.747	-2.818	-1.383	-1.779	-2.552	-0.303	-1.535
		(0.055)	(0.038)	(0.045)	(0.074)	(0.038)	(0.057)	(0.206)	(0.036)	(0.173)
Bus. Price Sens.	α_B	-0.113	-0.400	-0.335	-0.330	-0.075	-0.063	-0.282	-0.159	-0.335
		(0.024)	(0.029)	(0.037)	(0.046)	(0.017)	(0.019)	(0.033)	(0.016)	(0.111)
DoW Prefs	Mon.	0.285	0.049	-0.015	–	-0.120	0.142	-0.359	-0.014	-0.027
		(0.052)	(0.075)	(0.080)	–	(0.064)	(0.063)	(0.186)	(0.065)	(0.079)
	Tues.	0.143	0.230	–	-0.151	-0.081	-0.046	-0.350	-0.196	0.257
		(0.059)	(0.075)	–	(0.087)	(0.065)	(0.053)	(0.185)	(0.070)	(0.093)
	Wed.	–	0.181	-0.072	-0.256	-0.152	0.074	0.267	-0.216	0.140
		–	(0.074)	(0.084)	(0.090)	(0.103)	(0.051)	(0.165)	(0.068)	(0.110)
	Thurs.	-0.019	0.064	0.004	-0.678	-0.071	–	-0.016	-0.234	–
		(0.052)	(0.063)	(0.087)	(0.066)	(0.063)	–	(0.172)	(0.074)	–
	Fri.	-0.226	–	-0.102	-1.072	–	0.083	-0.179	-0.214	-0.193
		(0.051)	–	(0.083)	(0.068)	–	(0.050)	(0.173)	(0.069)	(0.076)
	Sat.	-0.254	0.011	-0.360	-0.947	0.307	-0.163	–	-0.317	-0.424
		(0.057)	(0.081)	(0.074)	(0.083)	(0.068)	(0.044)	–	(0.069)	(0.076)
	Sun.	0.332	0.405	-0.035	-0.239	-0.154	0.059	-0.137	–	-0.458
		(0.053)	(0.075)	(0.086)	(0.093)	(0.093)	(0.055)	(0.109)	–	(0.073)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.330	0.193	0.346	0.420	0.054	0.750	0.995	0.603	0.261
Summary										
Percent. of 0s		88.837	93.002	95.113	92.380	78.849	92.500	91.801	90.785	92.672
First stage R^2		0.788	0.655	0.735	0.745	0.437	0.830	0.789	0.780	0.670
Arrivals	A	2.064	0.859	1.677	1.306	2.807	1.809	3.293	3.015	1.133
Emp. Q	Q	0.319	0.180	0.179	0.394	0.402	0.339	0.149	0.188	0.461
		(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,3.00)
Model Q	$E[Q]$	0.318	0.178	0.182	0.389	0.399	0.343	0.158	0.195	0.454
		(0.04,1.00)	(0.01,0.63)	(0.02,0.67)	(0.02,1.56)	(0.03,1.48)	(0.06,1.03)	(0.04,0.42)	(0.04,0.60)	(0.02,2.09)
Elas	e	-0.934	-1.790	-2.241	-0.820	-2.870	-0.154	-1.092	-0.793	-1.433
		(-1.56,-0.21)	(-2.42,-0.99)	(-3.48,-1.38)	(-1.23,-0.42)	(-4.94,-1.44)	(-0.23,-0.09)	(-1.89,-0.69)	(-1.20,-0.60)	(-2.17,-0.50)
Number of Flights		597	636	630	898	301	1,011	51	266	966
Number of Dep. Dates		303	313	226	230	301	307	51	208	204
Number of Obs.		68,698	70,651	71,472	104,037	35,989	118,859	6,086	31,374	111,843

Note: For the “parameter” rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the “summary” rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled “Percent. of 0s”, the r-squared of a regression of prices on the controls and instruments is in “First stage R^2”, the mean of the estimated posterior distribution for the arrivals process is in “A”, the average total number of purchases observed in the data is in “Emp. Q” with the 5th and 95th percentile of purchases in parentheses, our model’s prediction of the average total number of purchases is in “Model Q” with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled “Elas”. Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 48: Demand Results Summary Table: Opportunity Cost Instrument

Route		78	79	80	81	82	83	84	85	86
Parameter										
Leis. Price Sens.	α_L	-1.381	-1.306	-0.828	-0.997	-2.043	-1.857	-1.145	-1.502	-0.719
		(0.109)	(0.036)	(0.085)	(0.046)	(0.129)	(0.105)	(0.073)	(0.041)	(0.114)
Bus. Price Sens.	α_B	-0.439	-0.064	-0.197	-0.225	-0.621	-0.955	-0.266	-0.215	-0.344
		(0.062)	(0.015)	(0.051)	(0.037)	(0.055)	(0.091)	(0.047)	(0.034)	(0.089)
DoW Prefs	Mon.	0.178	-0.094	0.024	-0.089	-0.108	–	–	0.385	-0.032
		(0.057)	(0.066)	(0.046)	(0.082)	(0.078)	–	–	(0.139)	(0.051)
	Tues.	-0.002	-0.098	0.184	–	-0.023	0.133	-0.250	-0.800	0.009
		(0.057)	(0.065)	(0.045)	–	(0.079)	(0.111)	(0.095)	(0.145)	(0.051)
	Wed.	-0.033	-0.387	0.200	0.120	-0.012	0.170	-0.293	-0.455	–
		(0.055)	(0.096)	(0.044)	(0.089)	(0.069)	(0.095)	(0.100)	(0.117)	–
	Thurs.	0.018	-0.027	0.060	0.031	–	0.436	-0.380	-0.332	-0.014
		(0.050)	(0.065)	(0.041)	(0.081)	–	(0.095)	(0.092)	(0.116)	(0.048)
	Fri.	0.030	–	-0.113	-0.025	0.038	0.433	-0.256	-0.390	0.441
		(0.054)	–	(0.037)	(0.076)	(0.054)	(0.095)	(0.090)	(0.127)	(0.107)
	Sat.	–	0.242	-0.228	-0.379	-0.369	-0.173	-0.322	-0.672	0.611
		–	(0.076)	(0.051)	(0.079)	(0.089)	(0.099)	(0.090)	(0.169)	(0.136)
	Sun.	0.329	-0.006	–	0.230	-0.106	0.071	-0.288	–	0.438
		(0.055)	(0.094)	–	(0.082)	(0.082)	(0.090)	(0.087)	–	(0.117)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.170	0.047	0.227	0.155	0.191	0.271	0.255	0.454	0.049
Summary										
Percent. of 0s		84.613	77.417	88.911	89.464	95.241	90.375	90.905	96.553	94.992
First stage R^2		0.825	0.443	0.743	0.830	0.664	0.891	0.756	0.746	0.643
Arrivals	A	2.509	2.937	2.390	1.067	0.654	0.780	0.817	0.379	3.946
Emp. Q	Q	0.293	0.441	0.642	0.165	0.189	0.154	0.124	0.222	0.168
		(0.00,2.00)	(0.00,3.00)	(0.00,3.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.295	0.441	0.642	0.160	0.191	0.151	0.124	0.216	0.188
		(0.04,1.06)	(0.03,1.66)	(0.06,2.40)	(0.02,0.54)	(0.02,0.72)	(0.01,0.60)	(0.01,0.43)	(0.01,1.06)	(0.05,0.50)
Elas	e	-1.533	-2.854	-0.806	-1.091	-1.962	-1.205	-1.008	-1.193	-3.099
		(-2.50,-0.78)	(-5.28,-1.41)	(-1.23,-0.35)	(-2.00,-0.46)	(-2.50,-0.88)	(-1.67,-0.65)	(-1.82,-0.37)	(-2.71,-0.29)	(-4.00,-2.09)
Number of Flights		489	301	1,371	391	1,219	310	282	679	632
Number of Dep. Dates		394	301	346	385	366	291	275	125	345
Number of Obs.		58,278	35,965	161,536	46,185	144,519	36,602	32,588	79,820	75,464

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 49: Demand Results Summary Table: Opportunity Cost Instrument

Route		87	88	89	90	91	92	93	94	95
Parameter										
Leis. Price Sens.	α_L	-2.456	-1.160	-1.834	-2.267	-2.255	-2.416	-2.525	-0.539	-1.565
		(0.195)	(0.056)	(0.078)	(0.081)	(0.191)	(0.097)	(0.100)	(0.051)	(0.152)
Bus. Price Sens.	α_B	-0.193	-0.316	-0.732	-0.307	-0.376	-0.194	-0.118	-0.204	-0.183
		(0.029)	(0.034)	(0.061)	(0.050)	(0.037)	(0.060)	(0.027)	(0.030)	(0.051)
DoW Prefs	Mon.	-0.235	–	0.158	0.555	-0.012	0.237	-0.118	0.196	–
		(0.079)	–	(0.039)	(0.100)	(0.103)	(0.142)	(0.051)	(0.075)	–
	Tues.	0.045	-0.046	0.068	0.138	0.428	–	-0.040	-0.108	0.061
		(0.095)	(0.063)	(0.053)	(0.136)	(0.125)	–	(0.059)	(0.078)	(0.126)
	Wed.	0.083	-0.040	0.170	0.448	0.496	0.148	–	0.026	-0.149
		(0.120)	(0.076)	(0.058)	(0.138)	(0.165)	(0.113)	–	(0.078)	(0.114)
	Thurs.	–	0.128	0.018	0.354	0.253	-0.143	-0.158	0.013	-0.055
		–	(0.071)	(0.057)	(0.107)	(0.111)	(0.101)	(0.052)	(0.079)	(0.131)
	Fri.	-0.255	0.002	–	-0.178	0.259	0.029	-0.337	–	-0.072
		(0.088)	(0.071)	–	(0.132)	(0.117)	(0.110)	(0.047)	–	(0.127)
	Sat.	-0.445	-0.117	-0.070	0.003	-0.186	-0.265	-0.319	0.220	-0.526
		(0.099)	(0.066)	(0.052)	(0.118)	(0.128)	(0.127)	(0.052)	(0.082)	(0.134)
	Sun.	-0.683	0.118	0.178	–	–	-0.160	-0.246	0.544	0.140
		(0.088)	(0.073)	(0.067)	–	–	(0.126)	(0.050)	(0.093)	(0.117)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.581	0.209	0.180	0.285	0.371	0.350	0.726	0.442	0.367
Summary										
Percent. of 0s		94.575	92.487	94.365	96.168	94.295	93.660	89.843	93.114	95.392
First stage R^2		0.612	0.722	0.685	0.632	0.647	0.730	0.769	0.805	0.621
Arrivals	A	0.660	1.169	1.311	0.252	0.854	0.523	2.245	2.901	0.363
Emp. Q	Q	0.187	0.266	0.297	0.098	0.333	0.156	0.554	0.117	0.112
		(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,3.00)	(0.00,1.00)	(0.00,1.00)
Model Q	$E[Q]$	0.187	0.265	0.300	0.097	0.327	0.154	0.555	0.123	0.110
		(0.01,0.67)	(0.03,0.83)	(0.03,1.13)	(0.00,0.48)	(0.01,1.41)	(0.01,0.61)	(0.05,2.04)	(0.03,0.31)	(0.01,0.36)
Elas	e	-0.572	-1.503	-1.145	-0.751	-1.364	-0.912	-0.336	-0.883	-1.268
		(-0.82,-0.31)	(-2.62,-0.63)	(-1.33,-0.88)	(-1.09,-0.33)	(-1.94,-0.61)	(-1.67,-0.35)	(-0.45,-0.15)	(-1.47,-0.54)	(-1.85,-0.46)
Number of Flights		846	751	1,546	595	574	621	1,403	209	478
Number of Dep. Dates		290	267	358	278	129	306	355	203	232
Number of Obs.		100,155	83,444	181,578	70,797	67,011	72,946	163,706	24,674	54,815

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 50: Demand Results Summary Table: Opportunity Cost Instrument

Route		96	97	98	99	100	101	102	103	104
Parameter										
Leis. Price Sens.	α_L	-1.005	-1.167	-2.591	-3.201	-0.994	-0.792	-0.292	-0.667	-2.547
		(0.077)	(0.143)	(0.287)	(0.174)	(0.213)	(0.048)	(0.016)	(0.032)	(0.121)
Bus. Price Sens.	α_B	-0.338	-0.249	-1.237	-0.370	-0.231	-0.096	-0.242	-0.102	-0.473
		(0.063)	(0.095)	(0.233)	(0.031)	(0.023)	(0.030)	(0.012)	(0.016)	(0.043)
DoW Prefs	Mon.	–	0.690	-0.342	0.296	-0.477	-0.599	–	0.059	0.196
		–	(0.110)	(0.092)	(0.075)	(0.085)	(0.096)	–	(0.049)	(0.090)
	Tues.	-0.207	0.703	-0.031	0.076	-0.295	-0.514	-0.211	-0.069	0.529
		(0.066)	(0.099)	(0.114)	(0.097)	(0.092)	(0.097)	(0.080)	(0.050)	(0.094)
	Wed.	-0.120	0.287	0.083	–	-0.349	-0.107	-0.103	-0.143	0.348
		(0.059)	(0.075)	(0.104)	–	(0.083)	(0.098)	(0.079)	(0.041)	(0.084)
	Thurs.	-0.078	0.112	-0.019	-0.056	–	0.067	0.022	-0.174	0.288
		(0.058)	(0.055)	(0.090)	(0.094)	–	(0.091)	(0.058)	(0.044)	(0.100)
	Fri.	0.077	–	–	-0.184	-0.095	–	0.040	-0.212	0.325
		(0.059)	–	–	(0.075)	(0.083)	–	(0.055)	(0.046)	(0.124)
	Sat.	-0.218	-0.234	-0.280	-0.348	-0.427	-0.180	0.262	-0.390	-0.095
		(0.056)	(0.081)	(0.106)	(0.086)	(0.081)	(0.087)	(0.054)	(0.044)	(0.119)
	Sun.	0.045	0.447	0.039	0.040	-0.187	-0.253	0.164	–	–
		(0.059)	(0.070)	(0.103)	(0.092)	(0.078)	(0.099)	(0.057)	–	–
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.328	0.323	0.219	0.574	0.994	0.060	0.498	0.228	0.584
Summary										
Percent. of 0s		89.775	91.536	92.862	92.082	91.195	92.083	85.475	87.280	94.381
First stage R^2		0.773	0.764	0.703	0.870	0.854	0.812	0.669	0.750	0.788
Arrivals	A	2.062	0.973	0.543	0.944	2.836	1.744	7.678	3.962	0.580
Emp. Q	Q	0.527	0.310	0.098	0.315	0.161	0.146	0.353	0.667	0.222
		(0.00,3.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,3.00)	(0.00,2.00)
Model Q	$E[Q]$	0.526	0.306	0.096	0.312	0.166	0.147	0.372	0.675	0.221
		(0.07,1.51)	(0.02,1.03)	(0.01,0.35)	(0.02,1.13)	(0.04,0.47)	(0.03,0.40)	(0.09,1.39)	(0.14,1.82)	(0.02,0.69)
Elas	e	-1.025	-1.381	-1.940	-0.690	-0.597	-1.018	-1.303	-0.787	-1.049
		(-1.79,-0.44)	(-2.49,-0.45)	(-2.63,-0.89)	(-0.96,-0.30)	(-1.45,-0.40)	(-2.29,-0.56)	(-2.12,-0.83)	(-1.45,-0.24)	(-1.38,-0.69)
Number of Flights		1,027	927	393	698	179	191	217	842	776
Number of Dep. Dates		286	330	392	228	171	177	217	245	221
Number of Obs.		118,307	105,706	46,999	80,735	20,705	22,749	25,914	94,552	86,314

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 51: Demand Results Summary Table: Opportunity Cost Instrument

Route		105	106	107	108	109	110	111	112	113
Parameter										
Leis. Price Sens.	α_L	-2.850	-1.050	-1.095	-0.949	-2.599	-2.892	-1.861	-0.817	-0.668
		(0.087)	(0.077)	(0.100)	(0.055)	(0.046)	(0.072)	(0.086)	(0.036)	(0.044)
Bus. Price Sens.	α_B	-0.133	-0.200	-0.221	-0.177	-0.148	-0.473	-0.105	-0.124	-0.108
		(0.044)	(0.047)	(0.038)	(0.034)	(0.037)	(0.054)	(0.026)	(0.023)	(0.017)
DoW Prefs	Mon.	0.037	-0.081	–	0.300	-0.137	-0.192	0.040	-0.010	0.140
		(0.094)	(0.085)	–	(0.075)	(0.044)	(0.127)	(0.062)	(0.045)	(0.057)
	Tues.	-0.242	-0.094	-0.010	0.222	–	0.078	0.009	–	–
		(0.101)	(0.085)	(0.066)	(0.080)	–	(0.117)	(0.070)	–	–
	Wed.	–	–	0.012	0.199	0.039	-0.206	0.099	0.177	0.004
		–	–	(0.064)	(0.084)	(0.048)	(0.116)	(0.070)	(0.056)	(0.052)
	Thurs.	0.301	0.124	-0.028	0.212	-0.066	–	0.183	0.188	0.092
		(0.103)	(0.082)	(0.054)	(0.072)	(0.049)	–	(0.068)	(0.053)	(0.056)
	Fri.	0.318	0.118	-0.012	0.233	-0.203	0.093	0.275	0.247	0.113
		(0.089)	(0.084)	(0.059)	(0.076)	(0.058)	(0.108)	(0.060)	(0.050)	(0.051)
	Sat.	-0.376	-0.216	-0.124	–	-0.500	-0.559	–	-0.224	-0.045
		(0.129)	(0.088)	(0.065)	–	(0.051)	(0.137)	–	(0.049)	(0.054)
	Sun.	-0.025	-0.091	0.107	0.782	-0.225	-0.479	-0.177	0.124	0.079
		(0.087)	(0.085)	(0.069)	(0.084)	(0.038)	(0.111)	(0.063)	(0.053)	(0.051)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.447	0.204	0.371	0.116	0.518	0.269	0.451	0.366	0.322
Summary										
Percent. of 0s		94.466	91.973	91.615	88.722	92.136	95.682	89.229	87.232	90.389
First stage R^2		0.742	0.749	0.752	0.817	0.752	0.828	0.781	0.756	0.773
Arrivals	A	0.641	0.667	1.479	1.088	2.710	0.268	1.854	3.757	1.775
Emp. Q	Q	0.180	0.110	0.256	0.179	0.488	0.102	0.291	0.670	0.264
		(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,3.00)	(0.00,1.00)	(0.00,2.00)	(0.00,3.00)	(0.00,2.00)
Model Q	$E[Q]$	0.178	0.109	0.257	0.174	0.494	0.100	0.288	0.678	0.265
		(0.01,0.63)	(0.01,0.37)	(0.04,0.76)	(0.02,0.60)	(0.05,1.65)	(0.00,0.47)	(0.03,0.92)	(0.15,1.77)	(0.04,0.75)
Elas	e	-0.501	-0.982	-1.178	-1.006	-0.375	-1.662	-0.544	-0.736	-0.836
		(-0.94,-0.21)	(-1.76,-0.27)	(-1.92,-0.45)	(-1.86,-0.40)	(-0.45,-0.27)	(-2.74,-0.39)	(-0.92,-0.18)	(-1.27,-0.24)	(-1.44,-0.29)
Number of Flights		976	396	753	381	1,528	711	582	823	767
Number of Dep. Dates		366	396	325	379	332	361	307	235	383
Number of Obs.		115,101	47,231	88,155	45,352	180,174	84,446	66,956	91,695	91,042

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 52: Demand Results Summary Table: Opportunity Cost Instrument

Route		114	115	116	117	118	119	120	121	122
Parameter										
Leis. Price Sens.	α_L	-2.086	-2.051	-2.430	-2.217	-0.857	-0.467	-1.967	-0.416	-1.864
		(0.038)	(0.103)	(0.045)	(0.076)	(0.120)	(0.018)	(0.064)	(0.044)	(0.082)
Bus. Price Sens.	α_B	-0.719	-0.864	-0.420	-0.353	-0.507	-0.171	-0.299	-0.182	-0.237
		(0.025)	(0.070)	(0.034)	(0.055)	(0.075)	(0.016)	(0.035)	(0.029)	(0.043)
DoW Prefs	Mon.	–	0.258	0.338	0.110	-0.078	0.146	–	-0.108	-0.080
		–	(0.059)	(0.129)	(0.080)	(0.081)	(0.059)	–	(0.068)	(0.043)
	Tues.	0.020	0.198	0.301	0.193	-0.122	–	0.078	-0.018	-0.040
		(0.077)	(0.076)	(0.136)	(0.065)	(0.078)	–	(0.059)	(0.068)	(0.041)
	Wed.	0.041	0.094	0.436	0.049	-0.066	0.018	0.009	–	–
		(0.067)	(0.089)	(0.114)	(0.048)	(0.063)	(0.059)	(0.065)	–	–
	Thurs.	0.062	0.033	0.308	0.034	0.357	0.175	-0.031	0.266	0.066
		(0.073)	(0.056)	(0.106)	(0.055)	(0.066)	(0.057)	(0.050)	(0.066)	(0.043)
	Fri.	-0.110	-0.213	0.081	–	0.025	0.130	-0.116	0.018	0.017
		(0.065)	(0.080)	(0.169)	–	(0.061)	(0.055)	(0.058)	(0.061)	(0.051)
	Sat.	-0.248	-0.181	–	-0.369	–	-0.111	-0.273	-0.176	-0.046
		(0.091)	(0.080)	–	(0.060)	–	(0.063)	(0.057)	(0.064)	(0.052)
	Sun.	-0.163	–	-0.133	0.154	-0.116	0.035	-0.031	-0.017	-0.012
		(0.073)	–	(0.141)	(0.080)	(0.060)	(0.059)	(0.051)	(0.064)	(0.049)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.217	0.207	0.505	0.586	0.211	0.222	0.458	0.264	0.859
Summary										
Percent. of 0s		95.189	95.218	94.883	94.222	90.562	88.211	92.180	90.319	94.976
First stage R^2		0.648	0.712	0.707	0.758	0.729	0.627	0.745	0.795	0.562
Arrivals	A	0.674	0.680	0.527	1.070	3.194	2.617	2.369	3.522	4.566
Emp. Q	Q	0.192	0.224	0.200	0.239	0.215	0.230	0.423	0.200	0.174
		(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.194	0.225	0.199	0.241	0.222	0.233	0.427	0.207	0.194
		(0.02,0.74)	(0.02,0.88)	(0.02,0.66)	(0.03,0.80)	(0.04,0.69)	(0.04,0.74)	(0.04,1.43)	(0.04,0.63)	(0.04,0.53)
Elas	e	-2.147	-2.220	-1.025	-0.793	-1.900	-0.884	-0.813	-0.996	-1.109
		(-2.79,-1.11)	(-3.04,-1.31)	(-1.37,-0.65)	(-0.98,-0.54)	(-2.55,-1.52)	(-1.47,-0.43)	(-1.00,-0.51)	(-1.54,-0.73)	(-1.61,-0.77)
Number of Flights		1,242	1,443	687	1,314	316	452	1,298	276	671
Number of Dep. Dates		371	363	198	384	210	378	314	215	362
Number of Obs.		147,288	170,376	77,032	155,366	37,711	53,729	150,869	32,599	80,043

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 53: Demand Results Summary Table: Opportunity Cost Instrument

Route		123	124	125	126	127	128	129	130	131
Parameter										
Leis. Price Sens.	α_L	-1.853	-2.348	-0.991	-1.430	-1.609	-0.489	-1.459	-1.170	-1.246
		(0.080)	(0.412)	(0.056)	(0.109)	(0.097)	(0.039)	(0.051)	(0.172)	(0.111)
Bus. Price Sens.	α_B	-0.633	-0.303	-0.138	-0.556	-0.623	-0.288	-0.259	-0.166	-0.400
		(0.029)	(0.041)	(0.028)	(0.086)	(0.053)	(0.031)	(0.032)	(0.039)	(0.075)
DoW Prefs	Mon.	-0.013	0.363	0.199	0.230	0.153	-0.281	–	0.580	0.154
		(0.057)	(0.091)	(0.095)	(0.043)	(0.089)	(0.093)	–	(0.070)	(0.075)
	Tues.	0.031	0.011	–	0.322	0.231	-0.428	-0.493	0.504	0.152
		(0.095)	(0.099)	–	(0.053)	(0.072)	(0.097)	(0.068)	(0.105)	(0.078)
	Wed.	0.080	0.201	–	0.235	0.288	-0.197	-0.558	0.073	0.129
		(0.076)	(0.090)	(0.097)	(0.052)	(0.094)	(0.083)	(0.068)	(0.078)	(0.085)
	Thurs.	–	0.321	-0.223	0.316	0.421	–	-0.350	0.325	-0.035
		–	(0.095)	(0.083)	(0.058)	(0.062)	–	(0.067)	(0.092)	(0.074)
	Fri.	-0.098	–	-0.183	0.301	0.049	-0.239	-0.694	0.282	-0.043
		(0.069)	–	(0.083)	(0.055)	(0.064)	(0.080)	(0.069)	(0.075)	(0.068)
	Sat.	-0.109	0.091	-0.305	–	–	-0.486	-0.837	–	0.035
		(0.064)	(0.084)	(0.088)	–	–	(0.087)	(0.072)	–	(0.076)
	Sun.	0.104	0.145	0.375	0.182	0.026	-0.338	0.292	0.223	–
		(0.068)	(0.091)	(0.089)	(0.050)	(0.088)	(0.086)	(0.071)	(0.085)	–
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.344	0.535	0.171	0.186	0.330	0.261	0.240	0.452	0.192
Summary										
Percent. of 0s		94.252	92.910	91.532	92.189	95.160	91.705	82.390	93.659	93.274
First stage R^2		0.677	0.834	0.785	0.742	0.741	0.779	0.800	0.713	0.652
Arrivals	A	1.367	0.824	0.668	2.803	0.681	2.082	1.560	1.024	0.784
Emp. Q	Q	0.309	0.085	0.116	0.493	0.228	0.128	0.307	0.291	0.170
		(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,3.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)
Model Q	$E[Q]$	0.314	0.085	0.114	0.503	0.231	0.130	0.297	0.290	0.168
		(0.04,1.13)	(0.02,0.23)	(0.01,0.40)	(0.06,1.68)	(0.02,0.89)	(0.01,0.41)	(0.04,1.10)	(0.04,0.87)	(0.01,0.59)
Elas	e	-1.521	-0.670	-1.033	-1.918	-1.539	-1.138	-1.692	-0.879	-1.421
		(-1.92,-1.15)	(-0.91,-0.50)	(-1.75,-0.24)	(-2.55,-1.13)	(-2.18,-0.92)	(-1.69,-0.74)	(-3.38,-0.34)	(-1.31,-0.34)	(-2.03,-0.71)
Number of Flights		1,403	371	397	1,495	1,372	196	391	790	622
Number of Dep. Dates		319	371	396	315	345	192	391	226	308
Number of Obs.		164,088	44,200	47,306	171,177	162,637	22,953	46,734	92,967	69,175

Note: For the “parameter” rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the “summary” rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled “Percent. of 0s”, the r-squared of a regression of prices on the controls and instruments is in “First stage R^2”, the mean of the estimated posterior distribution for the arrivals process is in “A”, the average total number of purchases observed in the data is in “Emp. Q” with the 5th and 95th percentile of purchases in parentheses, our model’s prediction of the average total number of purchases is in “Model Q” with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled “Elas”. Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 54: Demand Results Summary Table: Opportunity Cost Instrument

Route		132	133	134	135	136	137	138	139	140
Parameter										
Leis. Price Sens.	α_L	-1.707	-2.191	-1.093	-1.546	-1.352	-3.090	-1.890	-2.936	-1.412
		(0.103)	(0.122)	(0.052)	(0.101)	(0.063)	(0.176)	(0.044)	(0.217)	(0.068)
Bus. Price Sens.	α_B	-0.547	-1.233	-0.291	-0.239	-0.108	-0.398	-0.068	-0.330	-0.198
		(0.062)	(0.119)	(0.038)	(0.040)	(0.020)	(0.039)	(0.017)	(0.036)	(0.043)
DoW Prefs	Mon.	0.078	0.453	0.162	-0.037	0.183	-0.106	-0.262	-0.205	0.241
		(0.074)	(0.092)	(0.079)	(0.073)	(0.063)	(0.083)	(0.091)	(0.077)	(0.081)
	Tues.	-0.029	0.223	0.111	-0.222	-0.092	-0.082	-0.272	0.238	–
		(0.071)	(0.104)	(0.084)	(0.082)	(0.073)	(0.104)	(0.088)	(0.142)	–
	Wed.	0.208	–	0.199	-0.245	–	–	0.344	–	-0.214
		(0.085)	–	(0.079)	(0.091)	–	–	(0.092)	–	(0.074)
	Thurs.	0.075	0.066	0.195	-0.158	0.057	0.030	1.536	0.687	0.174
		(0.078)	(0.090)	(0.081)	(0.100)	(0.068)	(0.108)	(0.120)	(0.165)	(0.077)
	Fri.	0.173	0.018	0.331	-0.194	0.011	0.199	-0.278	-0.219	0.364
		(0.078)	(0.093)	(0.079)	(0.094)	(0.066)	(0.090)	(0.082)	(0.080)	(0.076)
	Sat.	–	-0.008	–	-0.330	-0.345	-0.201	-0.437	-0.418	-0.051
		–	(0.092)	–	(0.081)	(0.074)	(0.083)	(0.122)	(0.092)	(0.078)
	Sun.	0.101	0.118	0.262	–	0.019	-0.024	–	-0.605	-0.249
		(0.085)	(0.087)	(0.080)	–	(0.079)	(0.077)	–	(0.072)	(0.074)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.373	0.214	0.242	0.809	0.451	0.370	0.319	0.418	0.282
Summary										
Percent. of 0s		92.570	90.980	89.588	91.696	90.626	95.207	83.825	92.567	83.372
First stage R^2		0.834	0.817	0.754	0.799	0.793	0.762	0.735	0.759	0.778
Arrivals	A	1.066	0.755	0.893	2.307	1.103	1.450	0.988	1.249	1.121
Emp. Q	Q	0.221	0.146	0.155	0.127	0.244	0.170	0.283	0.397	0.283
		(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.220	0.143	0.150	0.130	0.240	0.172	0.268	0.391	0.266
		(0.02,0.80)	(0.01,0.57)	(0.02,0.51)	(0.02,0.39)	(0.03,0.69)	(0.02,0.60)	(0.02,1.06)	(0.02,1.58)	(0.04,0.92)
Elas	e	-1.287	-1.981	-1.221	-0.664	-0.780	-0.868	-1.357	-1.105	-1.394
		(-1.71,-0.67)	(-2.55,-1.22)	(-2.29,-0.40)	(-1.07,-0.49)	(-1.32,-0.20)	(-1.16,-0.66)	(-3.04,-0.13)	(-1.50,-0.68)	(-2.77,-0.20)
Number of Flights		623	318	389	191	671	718	336	794	387
Number of Dep. Dates		278	299	389	188	338	267	335	193	387
Number of Obs.		73,598	37,682	46,464	22,483	76,893	82,972	39,900	90,762	46,205

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 55: Demand Results Summary Table: Onward Connecting Traffic Instrument

Route		1	2	3	4	5	6	7	8	9	10
Parameter											
Leis. Price Sens.	α_L	-1.086	-1.215	-0.418	-0.574	-1.868	-1.193	-2.872	-1.312	-1.891	-2.022
		(0.073)	(0.150)	(0.018)	(0.026)	(0.126)	(0.124)	(0.170)	(0.093)	(0.088)	(0.224)
Bus. Price Sens.	α_B	-0.320	-0.603	-0.040	-0.182	-0.126	-0.326	-1.017	-0.098	-0.506	-0.304
		(0.055)	(0.101)	(0.007)	(0.019)	(0.020)	(0.044)	(0.187)	(0.025)	(0.069)	(0.085)
DoW Prefs	Mon.	0.054	-0.012	-0.189	-0.520	0.097	–	–	0.249	0.336	0.529
		(0.055)	(0.090)	(0.053)	(0.090)	(0.066)	–	–	(0.081)	(0.063)	(0.142)
	Tues.	-0.010	0.140	0.200	-0.426	-0.126	-0.132	-0.056	0.087	0.333	0.303
		(0.058)	(0.064)	(0.057)	(0.092)	(0.069)	(0.067)	(0.066)	(0.099)	(0.086)	(0.139)
	Wed.	0.139	0.138	0.290	-0.122	-0.095	-0.072	-0.077	–	0.272	0.531
		(0.061)	(0.054)	(0.051)	(0.094)	(0.063)	(0.073)	(0.075)	–	(0.075)	(0.162)
	Thurs.	0.131	0.067	0.314	-0.034	-0.165	-0.073	-0.097	-0.152	0.366	0.206
		(0.055)	(0.061)	(0.051)	(0.089)	(0.072)	(0.069)	(0.087)	(0.085)	(0.057)	(0.128)
	Fri.	0.161	0.074	0.186	–	–	-0.149	-0.280	-0.016	0.241	0.134
		(0.053)	(0.067)	(0.054)	–	–	(0.072)	(0.081)	(0.089)	(0.057)	(0.099)
	Sat.	–	-0.074	-0.035	0.014	-0.133	-0.112	-0.045	-0.289	-0.181	–
		–	(0.055)	(0.052)	(0.086)	(0.069)	(0.069)	(0.092)	(0.094)	(0.098)	–
	Sun.	0.081	–	–	-0.146	0.015	0.312	-0.011	-0.002	–	0.151
		(0.052)	–	–	(0.086)	(0.068)	(0.076)	(0.094)	(0.084)	–	(0.131)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.187	0.213	0.264	0.162	0.697	0.668	0.213	0.321	0.358	0.326
Summary											
Percent. of 0s		85.321	94.538	88.235	85.724	94.010	92.034	95.437	92.521	94.821	95.691
First stage R^2		0.828	0.690	0.614	0.730	0.820	0.771	0.868	0.777	0.655	0.587
Arrivals	A	2.470	1.017	1.894	3.570	3.912	2.920	0.617	0.703	0.893	0.358
Emp. Q	Q	0.279	0.226	0.228	0.249	0.195	0.172	0.095	0.192	0.243	0.104
		(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)
Model Q	$E[Q]$	0.281	0.230	0.229	0.253	0.210	0.178	0.096	0.188	0.243	0.103
		(0.03,1.02)	(0.03,0.79)	(0.04,0.71)	(0.07,0.79)	(0.04,0.64)	(0.03,0.54)	(0.01,0.39)	(0.02,0.67)	(0.02,0.88)	(0.01,0.35)
Elas	e	-1.458	-1.641	-0.833	-1.983	-0.479	-0.875	-1.494	-1.015	-1.343	-1.419
		(-2.47,-0.67)	(-2.61,-0.98)	(-1.37,-0.26)	(-2.97,-1.02)	(-0.74,-0.34)	(-1.24,-0.70)	(-1.86,-0.67)	(-1.47,-0.23)	(-1.70,-0.74)	(-2.08,-0.54)
Number of Flights		488	1,290	509	107	331	315	670	752	1,060	487
Number of Dep. Dates		393	379	393	107	163	203	392	387	274	238
Number of Obs.		58,076	156,777	60,721	12,791	38,847	37,319	79,955	89,486	124,843	56,307

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 56: Demand Results Summary Table: Onward Connecting Traffic Instrument

Route		11	12	13	14	15	16	17	18	19	20
Parameter											
Leis. Price Sens.	α_L	-2.866	-0.694	-0.834	-0.407	-1.911	-1.602	-1.423	-2.539	-1.990	-1.138
		(0.290)	(0.139)	(0.070)	(0.036)	(0.139)	(0.106)	(0.209)	(0.170)	(0.088)	(0.079)
Bus. Price Sens.	α_B	-0.143	-0.421	-0.210	-0.096	-0.399	-0.404	-0.099	-0.510	-0.081	-0.158
		(0.035)	(0.105)	(0.034)	(0.017)	(0.048)	(0.040)	(0.022)	(0.109)	(0.014)	(0.036)
DoW Prefs	Mon.	0.152	0.476	0.140	0.173	–	–	–	0.287	0.225	–
		(0.055)	(0.129)	(0.121)	(0.057)	–	–	–	(0.084)	(0.034)	–
	Tues.	0.272	-0.099	0.081	-0.042	-0.251	0.059	-0.072	0.242	0.213	-0.138
		(0.063)	(0.071)	(0.134)	(0.056)	(0.100)	(0.095)	(0.068)	(0.080)	(0.037)	(0.085)
	Wed.	0.133	0.064	-0.011	-0.043	-0.366	-0.014	-0.203	0.128	0.135	-0.169
		(0.058)	(0.075)	(0.131)	(0.060)	(0.095)	(0.080)	(0.062)	(0.079)	(0.032)	(0.082)
	Thurs.	0.045	–	-0.167	-0.018	-0.310	-0.003	-0.234	–	–	-0.245
		(0.048)	–	(0.125)	(0.058)	(0.090)	(0.070)	(0.064)	–	–	(0.077)
	Fri.	–	0.042	–	–	-0.338	-0.048	-0.355	-0.096	-0.146	-0.362
		–	(0.075)	–	–	(0.086)	(0.074)	(0.059)	(0.070)	(0.031)	(0.075)
	Sat.	-0.168	0.509	-0.065	-0.232	-0.256	-0.434	-0.341	-0.078	-0.123	-0.334
		(0.064)	(0.142)	(0.110)	(0.061)	(0.086)	(0.068)	(0.070)	(0.092)	(0.035)	(0.081)
	Sun.	-0.080	1.065	0.053	0.157	-0.445	-0.300	-0.278	0.469	-0.242	-0.271
		(0.048)	(0.206)	(0.108)	(0.053)	(0.079)	(0.074)	(0.064)	(0.105)	(0.029)	(0.076)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.543	0.188	0.171	0.262	0.335	0.266	0.394	0.219	0.461	0.485
Summary											
Percent. of 0s		90.947	84.530	94.297	88.374	90.659	91.792	90.133	93.015	86.994	91.174
First stage R^2		0.849	0.760	0.798	0.649	0.798	0.653	0.617	0.611	0.827	0.601
Arrivals	A	1.812	3.020	2.461	2.185	0.848	0.891	1.111	1.007	5.722	0.984
Emp. Q	Q	0.571	0.288	0.099	0.225	0.128	0.302	0.249	0.097	1.195	0.118
		(0.00,3.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,6.00)	(0.00,1.00)
Model Q	$E[Q]$	0.571	0.288	0.106	0.226	0.128	0.298	0.247	0.097	1.199	0.118
		(0.05,2.13)	(0.08,0.99)	(0.02,0.28)	(0.04,0.72)	(0.01,0.46)	(0.02,1.05)	(0.02,0.86)	(0.01,0.35)	(0.11,4.25)	(0.02,0.34)
Elas	e	-0.425	-1.963	-1.731	-0.762	-1.300	-1.793	-0.670	-1.321	-0.441	-0.682
		(-0.64,-0.17)	(-3.52,-0.90)	(-2.70,-0.94)	(-1.34,-0.35)	(-2.07,-0.46)	(-2.73,-0.65)	(-1.11,-0.17)	(-2.09,-0.51)	(-0.71,-0.17)	(-1.20,-0.27)
Number of Flights		1,453	217	123	444	304	960	647	335	1,712	391
Number of Dep. Dates		315	217	103	372	304	343	351	335	285	371
Number of Obs.		170,795	25,825	13,448	52,716	35,746	110,780	76,854	40,059	200,018	44,405

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 57: Demand Results Summary Table: Onward Connecting Traffic Instrument

Route		21	22	23	24	25	26	27	28	29	30
Parameter											
Leis. Price Sens.	α_L	-1.544	-0.511	-3.386	-1.001	-2.373	-1.083	-1.744	-0.741	-0.970	-1.968
		(0.062)	(0.268)	(0.148)	(0.062)	(0.086)	(0.083)	(0.056)	(0.055)	(0.102)	(0.086)
Bus. Price Sens.	α_B	-0.207	-0.024	-1.369	-0.115	-0.478	-0.179	-0.287	-0.168	-0.173	-0.073
		(0.031)	(0.005)	(0.155)	(0.022)	(0.023)	(0.033)	(0.055)	(0.022)	(0.032)	(0.019)
DoW Prefs	Mon.	0.239	–	-0.136	–	0.612	-0.223	–	0.092	-0.049	0.138
		(0.097)	–	(0.083)	–	(0.095)	(0.082)	–	(0.058)	(0.061)	(0.047)
	Tues.	-0.102	-0.174	–	-0.188	0.517	-0.255	-0.044	-0.093	-0.127	0.023
		(0.112)	(0.057)	–	(0.086)	(0.086)	(0.089)	(0.067)	(0.063)	(0.075)	(0.050)
	Wed.	-0.051	-0.277	0.090	-0.240	0.267	-0.134	0.078	-0.074	-0.014	0.135
		(0.104)	(0.053)	(0.088)	(0.094)	(0.085)	(0.087)	(0.059)	(0.059)	(0.065)	(0.052)
	Thurs.	0.079	-0.342	-0.107	-0.429	0.013	–	-0.123	-0.044	-0.037	0.086
		(0.101)	(0.055)	(0.088)	(0.083)	(0.081)	–	(0.071)	(0.052)	(0.055)	(0.050)
	Fri.	–	-0.422	-0.077	-0.311	-0.047	-0.134	-0.374	–	-0.148	–
		–	(0.056)	(0.077)	(0.079)	(0.087)	(0.087)	(0.053)	–	(0.056)	–
	Sat.	0.080	-0.397	0.188	-0.569	–	-0.277	-0.365	-0.086	-0.073	-0.376
		(0.130)	(0.062)	(0.090)	(0.081)	–	(0.081)	(0.048)	(0.056)	(0.058)	(0.053)
	Sun.	-0.047	0.022	0.592	-0.004	0.364	0.286	-0.054	0.345	–	-0.058
		(0.104)	(0.055)	(0.090)	(0.070)	(0.067)	(0.084)	(0.069)	(0.063)	–	(0.056)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.293	0.447	0.152	0.227	0.457	0.335	0.444	0.328	0.348	0.754
Summary											
Percent. of 0s		90.351	88.639	95.504	92.245	94.838	90.928	92.930	90.275	92.919	92.532
First stage R^2		0.691	0.632	0.880	0.780	0.705	0.612	0.728	0.748	0.781	0.844
Arrivals	A	0.599	1.857	0.572	0.682	0.925	0.969	1.805	1.614	1.551	1.870
Emp. Q	Q	0.134	0.222	0.093	0.198	0.242	0.120	0.549	0.315	0.307	0.332
		(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,3.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.132	0.221	0.094	0.194	0.243	0.119	0.551	0.317	0.310	0.337
		(0.01,0.51)	(0.04,0.66)	(0.01,0.38)	(0.02,0.68)	(0.02,0.86)	(0.02,0.35)	(0.04,2.17)	(0.04,0.93)	(0.05,0.91)	(0.05,1.01)
Elas	e	-1.415	-0.536	-1.883	-1.300	-1.182	-1.086	-0.959	-0.935	-0.934	-0.199
		(-2.36,-0.27)	(-0.87,-0.15)	(-2.21,-0.95)	(-2.23,-0.22)	(-1.48,-0.74)	(-1.77,-0.48)	(-1.32,-0.48)	(-1.54,-0.37)	(-1.38,-0.38)	(-0.28,-0.13)
Number of Flights		259	517	671	752	1,152	364	1,660	792	983	1,004
Number of Dep. Dates		258	394	393	387	298	347	279	322	307	308
Number of Obs.		30,531	61,710	80,066	89,341	135,404	41,459	195,980	91,287	116,084	118,320

Note: For the “parameter” rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the “summary” rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled “Percent. of 0s”, the r-squared of a regression of prices on the controls and instruments is in “First stage R^2”, the mean of the estimated posterior distribution for the arrivals process is in “A”, the average total number of purchases observed in the data is in “Emp. Q” with the 5th and 95th percentile of purchases in parentheses, our model’s prediction of the average total number of purchases is in “Model Q” with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled “Elas”. Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 58: Demand Results Summary Table: Onward Connecting Traffic Instrument

Route		31	32	33	34	35	36	37	38	39	40
Parameter											
Leis. Price Sens.	α_L	-2.037	-0.874	-0.715	-1.038	-1.830	-1.757	-2.856	-0.902	-2.220	-1.406
		(0.114)	(0.087)	(0.037)	(0.033)	(0.101)	(0.131)	(0.058)	(0.085)	(0.046)	(0.079)
Bus. Price Sens.	α_B	-0.280	-0.215	-0.192	-0.033	-0.233	-0.097	-0.431	-0.228	-0.288	-0.573
		(0.052)	(0.047)	(0.032)	(0.007)	(0.041)	(0.020)	(0.102)	(0.048)	(0.033)	(0.038)
DoW Prefs	Mon.	0.281	–	-0.044	-0.120	–	0.003	0.179	0.101	–	-0.101
		(0.143)	–	(0.056)	(0.051)	–	(0.068)	(0.107)	(0.065)	–	(0.072)
	Tues.	-0.031	-0.231	-0.252	-0.185	-0.212	–	0.187	-0.066	-0.020	-0.002
		(0.091)	(0.073)	(0.063)	(0.052)	(0.080)	–	(0.111)	(0.060)	(0.100)	(0.090)
	Wed.	–	-0.366	-0.184	–	-0.254	-0.008	–	–	0.006	0.100
		–	(0.065)	(0.071)	–	(0.093)	(0.070)	–	–	(0.095)	(0.078)
	Thurs.	-0.179	-0.271	-0.182	0.083	-0.466	0.001	-0.177	-0.061	-0.067	0.021
		(0.102)	(0.065)	(0.060)	(0.050)	(0.076)	(0.067)	(0.092)	(0.055)	(0.069)	(0.073)
	Fri.	-0.657	-0.379	-0.232	0.193	-0.397	-0.015	-0.066	-0.089	-0.181	–
		(0.077)	(0.059)	(0.058)	(0.051)	(0.090)	(0.062)	(0.126)	(0.056)	(0.066)	–
	Sat.	-0.546	-0.486	-0.271	0.828	-0.647	-0.079	-0.177	-0.217	-0.527	-0.105
		(0.101)	(0.063)	(0.065)	(0.062)	(0.102)	(0.069)	(0.108)	(0.059)	(0.081)	(0.078)
	Sun.	-0.137	0.040	–	0.341	0.020	0.132	0.256	0.207	-0.095	0.140
		(0.092)	(0.062)	–	(0.053)	(0.089)	(0.065)	(0.105)	(0.065)	(0.073)	(0.086)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.514	0.259	0.357	0.015	0.450	0.584	0.217	0.409	0.435	0.239
Summary											
Percent. of 0s		94.349	92.138	91.084	86.460	94.456	91.752	95.727	90.556	93.991	92.280
First stage R^2		0.682	0.721	0.746	0.654	0.739	0.740	0.736	0.764	0.720	0.846
Arrivals	A	0.682	1.160	1.174	6.800	0.602	1.518	0.276	1.789	0.996	1.050
Emp. Q	Q	0.194	0.282	0.225	0.300	0.181	0.255	0.101	0.255	0.250	0.232
		(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.194	0.282	0.225	0.320	0.180	0.256	0.100	0.257	0.252	0.231
		(0.01,0.69)	(0.04,0.86)	(0.03,0.68)	(0.07,1.16)	(0.02,0.62)	(0.04,0.75)	(0.00,0.47)	(0.04,0.72)	(0.03,0.79)	(0.02,0.83)
Elas	e	-0.407	-1.149	-0.939	-3.234	-0.891	-0.442	-1.830	-1.025	-0.957	-1.602
		(-0.56,-0.27)	(-1.89,-0.48)	(-1.61,-0.32)	(-5.18,-1.03)	(-1.30,-0.44)	(-0.75,-0.17)	(-2.89,-0.36)	(-1.63,-0.42)	(-1.30,-0.62)	(-2.80,-0.63)
Number of Flights		807	836	713	394	941	729	721	772	952	516
Number of Dep. Dates		276	309	373	389	354	311	365	386	279	221
Number of Obs.		95,441	98,207	84,575	47,069	111,049	85,158	85,695	91,643	110,327	58,546

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 59: Demand Results Summary Table: Onward Connecting Traffic Instrument

Route		41	42	43	44	45	46	47	48	49	50
Parameter											
Leis. Price Sens.	α_L	-0.912	-2.590	-0.831	-1.853	-1.726	-0.397	-0.851	-1.692	-3.830	-1.698
		(0.030)	(0.096)	(0.036)	(0.076)	(0.064)	(0.103)	(0.049)	(0.059)	(0.423)	(0.042)
Bus. Price Sens.	α_B	-0.186	-0.154	-0.111	-0.225	-0.143	-0.247	-0.103	-0.095	-0.119	-0.067
		(0.030)	(0.015)	(0.019)	(0.086)	(0.020)	(0.072)	(0.018)	(0.019)	(0.035)	(0.013)
DoW Prefs	Mon.	0.257	0.030	-0.057	0.070	0.179	-0.144	-0.111	-0.032	-0.106	1.957
		(0.078)	(0.055)	(0.053)	(0.049)	(0.062)	(0.077)	(0.073)	(0.034)	(0.089)	(0.134)
	Tues.	0.029	0.226	-0.118	0.198	0.266	-0.393	-0.144	0.103	–	0.531
		(0.079)	(0.043)	(0.058)	(0.053)	(0.064)	(0.080)	(0.076)	(0.037)	–	(0.092)
	Wed.	0.152	0.145	-0.041	0.227	0.257	-0.248	0.018	0.229	0.222	0.171
		(0.079)	(0.050)	(0.056)	(0.057)	(0.054)	(0.074)	(0.085)	(0.044)	(0.128)	(0.086)
	Thurs.	-0.020	0.070	0.039	0.089	0.133	0.038	0.097	0.229	0.143	-0.042
		(0.076)	(0.052)	(0.056)	(0.050)	(0.064)	(0.063)	(0.069)	(0.038)	(0.104)	(0.085)
	Fri.	–	-0.205	-0.034	-0.083	0.150	–	-0.058	-0.035	-0.282	–
		–	(0.059)	(0.049)	(0.054)	(0.048)	–	(0.073)	(0.029)	(0.094)	–
	Sat.	-0.184	-0.266	-0.144	-0.209	–	0.101	–	-0.087	-0.574	-0.212
		(0.075)	(0.061)	(0.051)	(0.050)	–	(0.073)	–	(0.035)	(0.092)	(0.129)
	Sun.	0.402	–	–	–	0.191	-0.191	0.016	–	-0.294	-0.219
		(0.075)	–	–	–	(0.065)	(0.064)	(0.072)	–	(0.123)	(0.089)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.279	0.520	0.266	0.440	0.443	0.494	0.291	0.448	0.550	0.320
Summary											
Percent. of 0s		88.584	92.883	90.439	92.235	90.800	84.262	90.305	86.333	90.623	83.368
First stage R^2		0.775	0.741	0.793	0.735	0.853	0.733	0.630	0.786	0.776	0.800
Arrivals	A	0.900	1.812	1.592	2.222	1.859	3.562	1.061	5.634	0.789	0.983
Emp. Q	Q	0.170	0.553	0.302	0.419	0.578	0.310	0.244	1.238	0.330	0.316
		(0.00,1.00)	(0.00,3.00)	(0.00,2.00)	(0.00,2.00)	(0.00,3.00)	(0.00,2.00)	(0.00,2.00)	(0.00,6.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.165	0.551	0.303	0.422	0.580	0.310	0.242	1.242	0.326	0.290
		(0.02,0.56)	(0.03,2.16)	(0.04,0.89)	(0.04,1.43)	(0.04,2.23)	(0.08,1.10)	(0.02,0.85)	(0.12,4.39)	(0.01,1.42)	(0.02,1.17)
Elas	e	-0.988	-0.405	-0.981	-0.919	-0.591	-0.940	-0.633	-0.543	-0.435	-1.301
		(-1.92,-0.24)	(-0.72,-0.19)	(-1.73,-0.27)	(-1.25,-0.43)	(-0.82,-0.23)	(-1.42,-0.45)	(-1.26,-0.17)	(-0.78,-0.20)	(-0.80,-0.14)	(-3.05,-0.13)
Number of Flights		390	1,641	876	1,462	1,387	221	659	1,703	559	333
Number of Dep. Dates		390	276	375	359	301	221	355	284	214	333
Number of Obs.		46,582	194,693	103,754	173,340	162,964	26,363	77,914	204,289	66,438	39,701

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 60: Demand Results Summary Table: Onward Connecting Traffic Instrument

Route		51	52	53	54	55	56	57	58	59
Parameter										
Leis. Price Sens.	α_L	-3.305	-2.226	-0.253	-0.574	-2.238	-0.627	-1.635	-1.892	-1.997
		(0.201)	(0.233)	(0.019)	(0.052)	(0.120)	(0.051)	(0.079)	(0.119)	(0.030)
Bus. Price Sens.	α_B	-0.427	-0.272	-0.086	-0.179	-0.238	-0.263	-0.272	-0.300	-0.819
		(0.033)	(0.032)	(0.013)	(0.033)	(0.044)	(0.033)	(0.055)	(0.045)	(0.043)
DoW Prefs	Mon.	-0.301	0.012	-0.231	-0.026	–	0.106	0.310	0.214	0.359
		(0.100)	(0.116)	(0.045)	(0.087)	–	(0.111)	(0.094)	(0.115)	(0.083)
	Tues.	–	-0.110	-0.166	0.187	-0.009	-0.020	0.041	-0.073	0.473
		–	(0.119)	(0.045)	(0.094)	(0.069)	(0.105)	(0.101)	(0.114)	(0.088)
	Wed.	0.283	0.080	-0.187	0.118	0.048	0.223	-0.075	–	0.388
		(0.099)	(0.110)	(0.045)	(0.092)	(0.058)	(0.102)	(0.093)	–	(0.091)
	Thurs.	0.039	-0.040	-0.136	0.052	0.231	0.275	–	0.131	0.217
		(0.143)	(0.117)	(0.044)	(0.086)	(0.070)	(0.095)	–	(0.115)	(0.081)
	Fri.	-0.110	-0.155	-0.033	–	0.084	0.142	-0.315	-0.003	–
		(0.158)	(0.110)	(0.041)	–	(0.076)	(0.100)	(0.083)	(0.114)	–
	Sat.	-0.355	-0.135	–	-0.020	0.074	0.016	-0.335	-0.055	-0.081
		(0.119)	(0.093)	–	(0.087)	(0.071)	(0.086)	(0.093)	(0.134)	(0.073)
	Sun.	-0.502	–	-0.052	0.353	0.067	–	0.386	0.481	0.218
		(0.105)	–	(0.042)	(0.086)	(0.071)	–	(0.085)	(0.117)	(0.069)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.441	0.752	0.292	0.142	0.661	0.416	0.366	0.355	0.208
Summary										
Percent. of 0s		95.353	93.047	81.276	85.095	93.798	93.640	89.817	89.906	95.291
First stage R^2		0.751	0.809	0.669	0.569	0.763	0.763	0.794	0.740	0.708
Arrivals	A	0.595	3.127	6.387	3.884	4.804	2.706	0.837	0.578	0.654
Emp. Q	Q	0.164	0.115	0.369	0.262	0.193	0.115	0.143	0.142	0.166
		(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)
Model Q	$E[Q]$	0.166	0.121	0.379	0.266	0.210	0.122	0.142	0.140	0.167
		(0.01,0.71)	(0.02,0.31)	(0.13,1.27)	(0.07,0.84)	(0.04,0.66)	(0.03,0.32)	(0.01,0.51)	(0.01,0.55)	(0.01,0.71)
Elas	e	-1.840	-0.891	-0.840	-1.860	-0.819	-1.226	-1.083	-1.431	-2.314
		(-2.38,-1.03)	(-1.37,-0.56)	(-1.27,-0.54)	(-2.58,-0.94)	(-1.24,-0.59)	(-2.03,-0.74)	(-1.92,-0.29)	(-2.43,-0.38)	(-3.22,-1.30)
Number of Flights		854	96	396	107	374	145	311	260	927
Number of Dep. Dates		291	96	396	107	194	117	311	260	317
Number of Obs.		100,922	11,463	47,336	12,774	44,311	15,440	36,570	30,454	109,772

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 61: Demand Results Summary Table: Onward Connecting Traffic Instrument

Route		60	61	62	63	64	65	66	67	68
Parameter										
Leis. Price Sens.	α_L	-0.667	-1.214	-1.855	-1.220	-1.368	-1.971	-2.472	-2.306	-0.764
		(0.119)	(0.249)	(0.029)	(0.091)	(0.055)	(0.086)	(0.091)	(0.045)	(0.149)
Bus. Price Sens.	α_B	-0.389	-0.487	-0.593	-0.305	-0.248	-0.502	-0.370	-0.647	-0.269
		(0.042)	(0.054)	(0.030)	(0.062)	(0.029)	(0.070)	(0.062)	(0.061)	(0.031)
DoW Prefs	Mon.	–	-0.361	0.168	–	-0.176	0.544	-0.058	0.899	-0.340
		–	(0.174)	(0.083)	–	(0.112)	(0.120)	(0.140)	(0.132)	(0.080)
	Tues.	-0.194	-0.685	0.219	-0.108	-0.302	0.387	–	0.663	-0.321
		(0.112)	(0.165)	(0.070)	(0.100)	(0.127)	(0.106)	–	(0.153)	(0.082)
	Wed.	0.241	–	0.121	0.072	–	0.501	-0.174	0.652	–
		(0.105)	–	(0.081)	(0.097)	–	(0.100)	(0.121)	(0.113)	–
	Thurs.	-0.027	0.101	-0.192	0.079	0.420	0.194	-0.352	0.129	0.001
		(0.107)	(0.158)	(0.083)	(0.094)	(0.109)	(0.135)	(0.131)	(0.119)	(0.075)
	Fri.	0.107	-0.151	-0.708	-0.199	0.145	–	-0.725	-0.060	-0.158
		(0.106)	(0.156)	(0.079)	(0.086)	(0.087)	–	(0.095)	(0.110)	(0.079)
	Sat.	0.024	-0.097	-0.627	-0.300	0.009	-0.268	-0.445	–	-0.288
		(0.106)	(0.125)	(0.074)	(0.099)	(0.117)	(0.115)	(0.116)	–	(0.082)
	Sun.	-0.196	-0.366	–	0.419	-0.101	0.306	0.141	0.690	-0.121
		(0.101)	(0.133)	–	(0.100)	(0.118)	(0.112)	(0.148)	(0.144)	(0.079)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.520	0.873	0.278	0.238	0.505	0.457	0.328	0.324	0.662
Summary										
Percent. of 0s		93.403	93.125	92.490	90.095	96.403	96.128	96.326	94.233	93.029
First stage R^2		0.726	0.686	0.703	0.799	0.736	0.700	0.623	0.695	0.780
Arrivals	A	3.060	4.622	1.226	0.876	0.388	0.337	0.253	0.884	3.508
Emp. Q	Q	0.117	0.142	0.474	0.136	0.230	0.130	0.096	0.340	0.119
		(0.00,1.00)	(0.00,1.00)	(0.00,3.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)
Model Q	$E[Q]$	0.124	0.154	0.468	0.136	0.224	0.129	0.096	0.334	0.126
		(0.02,0.34)	(0.03,0.38)	(0.02,2.09)	(0.01,0.49)	(0.00,1.05)	(0.00,0.63)	(0.00,0.49)	(0.02,1.40)	(0.03,0.32)
Elas	e	-1.186	-1.646	-1.774	-1.148	-1.003	-0.988	-1.358	-1.770	-0.864
		(-1.73,-0.82)	(-3.27,-1.03)	(-2.57,-0.88)	(-2.03,-0.48)	(-2.41,-0.26)	(-1.41,-0.58)	(-2.11,-0.58)	(-2.67,-0.71)	(-1.32,-0.51)
Number of Flights		117	53	1,120	283	709	965	671	602	211
Number of Dep. Dates		117	53	236	277	131	351	302	133	205
Number of Obs.		13,960	6,342	129,887	32,711	83,245	114,462	79,617	70,103	25,005

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 62: Demand Results Summary Table: Onward Connecting Traffic Instrument

Route		69	70	71	72	73	74	75	76	77
Parameter										
Leis. Price Sens.	α_L	-1.090	-1.197	-1.747	-2.818	-1.383	-1.779	-2.552	-0.303	-1.535
		(0.055)	(0.038)	(0.045)	(0.074)	(0.038)	(0.057)	(0.206)	(0.036)	(0.173)
Bus. Price Sens.	α_B	-0.113	-0.400	-0.335	-0.330	-0.075	-0.063	-0.282	-0.159	-0.335
		(0.024)	(0.029)	(0.037)	(0.046)	(0.017)	(0.019)	(0.033)	(0.016)	(0.111)
DoW Prefs	Mon.	0.285	0.049	-0.015	–	-0.120	0.142	-0.359	-0.014	-0.027
		(0.052)	(0.075)	(0.080)	–	(0.064)	(0.063)	(0.186)	(0.065)	(0.079)
	Tues.	0.143	0.230	–	-0.151	-0.081	-0.046	-0.350	-0.196	0.257
		(0.059)	(0.075)	–	(0.087)	(0.065)	(0.053)	(0.185)	(0.070)	(0.093)
	Wed.	–	0.181	-0.072	-0.256	-0.152	0.074	0.267	-0.216	0.140
		–	(0.074)	(0.084)	(0.090)	(0.103)	(0.051)	(0.165)	(0.068)	(0.110)
	Thurs.	-0.019	0.064	0.004	-0.678	-0.071	–	-0.016	-0.234	–
		(0.052)	(0.063)	(0.087)	(0.066)	(0.063)	–	(0.172)	(0.074)	–
	Fri.	-0.226	–	-0.102	-1.072	–	0.083	-0.179	-0.214	-0.193
		(0.051)	–	(0.083)	(0.068)	–	(0.050)	(0.173)	(0.069)	(0.076)
	Sat.	-0.254	0.011	-0.360	-0.947	0.307	-0.163	–	-0.317	-0.424
		(0.057)	(0.081)	(0.074)	(0.083)	(0.068)	(0.044)	–	(0.069)	(0.076)
	Sun.	0.332	0.405	-0.035	-0.239	-0.154	0.059	-0.137	–	-0.458
		(0.053)	(0.075)	(0.086)	(0.093)	(0.093)	(0.055)	(0.109)	–	(0.073)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.330	0.193	0.346	0.420	0.054	0.750	0.995	0.603	0.261
Summary										
Percent. of 0s		88.837	93.002	95.113	92.380	78.849	92.500	91.801	90.785	92.672
First stage R^2		0.788	0.655	0.735	0.745	0.437	0.830	0.789	0.780	0.670
Arrivals	A	2.064	0.859	1.677	1.306	2.807	1.809	3.293	3.015	1.133
Emp. Q	Q	0.319	0.180	0.179	0.394	0.402	0.339	0.149	0.188	0.461
		(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,3.00)
Model Q	$E[Q]$	0.318	0.178	0.182	0.389	0.399	0.343	0.158	0.195	0.454
		(0.04,1.00)	(0.01,0.63)	(0.02,0.67)	(0.02,1.56)	(0.03,1.48)	(0.06,1.03)	(0.04,0.42)	(0.04,0.60)	(0.02,2.09)
Elas	e	-0.934	-1.790	-2.241	-0.820	-2.870	-0.154	-1.092	-0.793	-1.433
		(-1.56,-0.21)	(-2.42,-0.99)	(-3.48,-1.38)	(-1.23,-0.42)	(-4.94,-1.44)	(-0.23,-0.09)	(-1.89,-0.69)	(-1.20,-0.60)	(-2.17,-0.50)
Number of Flights		597	636	630	898	301	1,011	51	266	966
Number of Dep. Dates		303	313	226	230	301	307	51	208	204
Number of Obs.		68,698	70,651	71,472	104,037	35,989	118,859	6,086	31,374	111,843

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 63: Demand Results Summary Table: Onward Connecting Traffic Instrument

Route		78	79	80	81	82	83	84	85	86
Parameter										
Leis. Price Sens.	α_L	-1.381	-1.306	-0.828	-0.997	-2.043	-1.857	-1.145	-1.502	-0.719
		(0.109)	(0.036)	(0.085)	(0.046)	(0.129)	(0.105)	(0.073)	(0.041)	(0.114)
Bus. Price Sens.	α_B	-0.439	-0.064	-0.197	-0.225	-0.621	-0.955	-0.266	-0.215	-0.344
		(0.062)	(0.015)	(0.051)	(0.037)	(0.055)	(0.091)	(0.047)	(0.034)	(0.089)
DoW Prefs	Mon.	0.178	-0.094	0.024	-0.089	-0.108	–	–	0.385	-0.032
		(0.057)	(0.066)	(0.046)	(0.082)	(0.078)	–	–	(0.139)	(0.051)
	Tues.	-0.002	-0.098	0.184	–	-0.023	0.133	-0.250	-0.800	0.009
		(0.057)	(0.065)	(0.045)	–	(0.079)	(0.111)	(0.095)	(0.145)	(0.051)
	Wed.	-0.033	-0.387	0.200	0.120	-0.012	0.170	-0.293	-0.455	–
		(0.055)	(0.096)	(0.044)	(0.089)	(0.069)	(0.095)	(0.100)	(0.117)	–
	Thurs.	0.018	-0.027	0.060	0.031	–	0.436	-0.380	-0.332	-0.014
		(0.050)	(0.065)	(0.041)	(0.081)	–	(0.095)	(0.092)	(0.116)	(0.048)
	Fri.	0.030	–	-0.113	-0.025	0.038	0.433	-0.256	-0.390	0.441
		(0.054)	–	(0.037)	(0.076)	(0.054)	(0.095)	(0.090)	(0.127)	(0.107)
	Sat.	–	0.242	-0.228	-0.379	-0.369	-0.173	-0.322	-0.672	0.611
		–	(0.076)	(0.051)	(0.079)	(0.089)	(0.099)	(0.090)	(0.169)	(0.136)
	Sun.	0.329	-0.006	–	0.230	-0.106	0.071	-0.288	–	0.438
		(0.055)	(0.094)	–	(0.082)	(0.082)	(0.090)	(0.087)	–	(0.117)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.170	0.047	0.227	0.155	0.191	0.271	0.255	0.454	0.049
Summary										
Percent. of 0s		84.613	77.417	88.911	89.464	95.241	90.375	90.905	96.553	94.992
First stage R^2		0.825	0.443	0.743	0.830	0.664	0.891	0.756	0.746	0.643
Arrivals	A	2.509	2.937	2.390	1.067	0.654	0.780	0.817	0.379	3.946
Emp. Q	Q	0.293	0.441	0.642	0.165	0.189	0.154	0.124	0.222	0.168
		(0.00,2.00)	(0.00,3.00)	(0.00,3.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.295	0.441	0.642	0.160	0.191	0.151	0.124	0.216	0.188
		(0.04,1.06)	(0.03,1.66)	(0.06,2.40)	(0.02,0.54)	(0.02,0.72)	(0.01,0.60)	(0.01,0.43)	(0.01,1.06)	(0.05,0.50)
Elas	e	-1.533	-2.854	-0.806	-1.091	-1.962	-1.205	-1.008	-1.193	-3.099
		(-2.50,-0.78)	(-5.28,-1.41)	(-1.23,-0.35)	(-2.00,-0.46)	(-2.50,-0.88)	(-1.67,-0.65)	(-1.82,-0.37)	(-2.71,-0.29)	(-4.00,-2.09)
Number of Flights		489	301	1,371	391	1,219	310	282	679	632
Number of Dep. Dates		394	301	346	385	366	291	275	125	345
Number of Obs.		58,278	35,965	161,536	46,185	144,519	36,602	32,588	79,820	75,464

Note: For the “parameter” rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the “summary” rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled “Percent. of 0s”, the r-squared of a regression of prices on the controls and instruments is in “First stage R^2”, the mean of the estimated posterior distribution for the arrivals process is in “A”, the average total number of purchases observed in the data is in “Emp. Q” with the 5th and 95th percentile of purchases in parentheses, our model’s prediction of the average total number of purchases is in “Model Q” with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled “Elas”. Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 64: Demand Results Summary Table: Onward Connecting Traffic Instrument

Route		87	88	89	90	91	92	93	94	95
Parameter										
Leis. Price Sens.	α_L	-2.456	-1.160	-1.834	-2.267	-2.255	-2.416	-2.525	-0.539	-1.565
		(0.195)	(0.056)	(0.078)	(0.081)	(0.191)	(0.097)	(0.100)	(0.051)	(0.152)
Bus. Price Sens.	α_B	-0.193	-0.316	-0.732	-0.307	-0.376	-0.194	-0.118	-0.204	-0.183
		(0.029)	(0.034)	(0.061)	(0.050)	(0.037)	(0.060)	(0.027)	(0.030)	(0.051)
DoW Prefs	Mon.	-0.235	–	0.158	0.555	-0.012	0.237	-0.118	0.196	–
		(0.079)	–	(0.039)	(0.100)	(0.103)	(0.142)	(0.051)	(0.075)	–
	Tues.	0.045	-0.046	0.068	0.138	0.428	–	-0.040	-0.108	0.061
		(0.095)	(0.063)	(0.053)	(0.136)	(0.125)	–	(0.059)	(0.078)	(0.126)
	Wed.	0.083	-0.040	0.170	0.448	0.496	0.148	–	0.026	-0.149
		(0.120)	(0.076)	(0.058)	(0.138)	(0.165)	(0.113)	–	(0.078)	(0.114)
	Thurs.	–	0.128	0.018	0.354	0.253	-0.143	-0.158	0.013	-0.055
		–	(0.071)	(0.057)	(0.107)	(0.111)	(0.101)	(0.052)	(0.079)	(0.131)
	Fri.	-0.255	0.002	–	-0.178	0.259	0.029	-0.337	–	-0.072
		(0.088)	(0.071)	–	(0.132)	(0.117)	(0.110)	(0.047)	–	(0.127)
	Sat.	-0.445	-0.117	-0.070	0.003	-0.186	-0.265	-0.319	0.220	-0.526
		(0.099)	(0.066)	(0.052)	(0.118)	(0.128)	(0.127)	(0.052)	(0.082)	(0.134)
	Sun.	-0.683	0.118	0.178	–	–	-0.160	-0.246	0.544	0.140
		(0.088)	(0.073)	(0.067)	–	–	(0.126)	(0.050)	(0.093)	(0.117)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.581	0.209	0.180	0.285	0.371	0.350	0.726	0.442	0.367
Summary										
Percent. of 0s		94.575	92.487	94.365	96.168	94.295	93.660	89.843	93.114	95.392
First stage R^2		0.612	0.722	0.685	0.632	0.647	0.730	0.769	0.805	0.621
Arrivals	A	0.660	1.169	1.311	0.252	0.854	0.523	2.245	2.901	0.363
Emp. Q	Q	0.187	0.266	0.297	0.098	0.333	0.156	0.554	0.117	0.112
		(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,3.00)	(0.00,1.00)	(0.00,1.00)
Model Q	$E[Q]$	0.187	0.265	0.300	0.097	0.327	0.154	0.555	0.123	0.110
		(0.01,0.67)	(0.03,0.83)	(0.03,1.13)	(0.00,0.48)	(0.01,1.41)	(0.01,0.61)	(0.05,2.04)	(0.03,0.31)	(0.01,0.36)
Elas	e	-0.572	-1.503	-1.145	-0.751	-1.364	-0.912	-0.336	-0.883	-1.268
		(-0.82,-0.31)	(-2.62,-0.63)	(-1.33,-0.88)	(-1.09,-0.33)	(-1.94,-0.61)	(-1.67,-0.35)	(-0.45,-0.15)	(-1.47,-0.54)	(-1.85,-0.46)
Number of Flights		846	751	1,546	595	574	621	1,403	209	478
Number of Dep. Dates		290	267	358	278	129	306	355	203	232
Number of Obs.		100,155	83,444	181,578	70,797	67,011	72,946	163,706	24,674	54,815

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 65: Demand Results Summary Table: Onward Connecting Traffic Instrument

Route		96	97	98	99	100	101	102	103	104
Parameter										
Leis. Price Sens.	α_L	-1.005	-1.167	-2.591	-3.201	-0.994	-0.792	-0.292	-0.667	-2.547
		(0.077)	(0.143)	(0.287)	(0.174)	(0.213)	(0.048)	(0.016)	(0.032)	(0.121)
Bus. Price Sens.	α_B	-0.338	-0.249	-1.237	-0.370	-0.231	-0.096	-0.242	-0.102	-0.473
		(0.063)	(0.095)	(0.233)	(0.031)	(0.023)	(0.030)	(0.012)	(0.016)	(0.043)
DoW Prefs	Mon.	–	0.690	-0.342	0.296	-0.477	-0.599	–	0.059	0.196
		–	(0.110)	(0.092)	(0.075)	(0.085)	(0.096)	–	(0.049)	(0.090)
	Tues.	-0.207	0.703	-0.031	0.076	-0.295	-0.514	-0.211	-0.069	0.529
		(0.066)	(0.099)	(0.114)	(0.097)	(0.092)	(0.097)	(0.080)	(0.050)	(0.094)
	Wed.	-0.120	0.287	0.083	–	-0.349	-0.107	-0.103	-0.143	0.348
		(0.059)	(0.075)	(0.104)	–	(0.083)	(0.098)	(0.079)	(0.041)	(0.084)
	Thurs.	-0.078	0.112	-0.019	-0.056	–	0.067	0.022	-0.174	0.288
		(0.058)	(0.055)	(0.090)	(0.094)	–	(0.091)	(0.058)	(0.044)	(0.100)
	Fri.	0.077	–	–	-0.184	-0.095	–	0.040	-0.212	0.325
		(0.059)	–	–	(0.075)	(0.083)	–	(0.055)	(0.046)	(0.124)
	Sat.	-0.218	-0.234	-0.280	-0.348	-0.427	-0.180	0.262	-0.390	-0.095
		(0.056)	(0.081)	(0.106)	(0.086)	(0.081)	(0.087)	(0.054)	(0.044)	(0.119)
	Sun.	0.045	0.447	0.039	0.040	-0.187	-0.253	0.164	–	–
		(0.059)	(0.070)	(0.103)	(0.092)	(0.078)	(0.099)	(0.057)	–	–
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.328	0.323	0.219	0.574	0.994	0.060	0.498	0.228	0.584
Summary										
Percent. of 0s		89.775	91.536	92.862	92.082	91.195	92.083	85.475	87.280	94.381
First stage R^2		0.773	0.764	0.703	0.870	0.854	0.812	0.669	0.750	0.788
Arrivals	A	2.062	0.973	0.543	0.944	2.836	1.744	7.678	3.962	0.580
Emp. Q	Q	0.527	0.310	0.098	0.315	0.161	0.146	0.353	0.667	0.222
		(0.00,3.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,3.00)	(0.00,2.00)
Model Q	$E[Q]$	0.526	0.306	0.096	0.312	0.166	0.147	0.372	0.675	0.221
		(0.07,1.51)	(0.02,1.03)	(0.01,0.35)	(0.02,1.13)	(0.04,0.47)	(0.03,0.40)	(0.09,1.39)	(0.14,1.82)	(0.02,0.69)
Elas	e	-1.025	-1.381	-1.940	-0.690	-0.597	-1.018	-1.303	-0.787	-1.049
		(-1.79,-0.44)	(-2.49,-0.45)	(-2.63,-0.89)	(-0.96,-0.30)	(-1.45,-0.40)	(-2.29,-0.56)	(-2.12,-0.83)	(-1.45,-0.24)	(-1.38,-0.69)
Number of Flights		1,027	927	393	698	179	191	217	842	776
Number of Dep. Dates		286	330	392	228	171	177	217	245	221
Number of Obs.		118,307	105,706	46,999	80,735	20,705	22,749	25,914	94,552	86,314

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 66: Demand Results Summary Table: Onward Connecting Traffic Instrument

Route		105	106	107	108	109	110	111	112	113
Parameter										
Leis. Price Sens.	α_L	-2.850	-1.050	-1.095	-0.949	-2.599	-2.892	-1.861	-0.817	-0.668
		(0.087)	(0.077)	(0.100)	(0.055)	(0.046)	(0.072)	(0.086)	(0.036)	(0.044)
Bus. Price Sens.	α_B	-0.133	-0.200	-0.221	-0.177	-0.148	-0.473	-0.105	-0.124	-0.108
		(0.044)	(0.047)	(0.038)	(0.034)	(0.037)	(0.054)	(0.026)	(0.023)	(0.017)
DoW Prefs	Mon.	0.037	-0.081	–	0.300	-0.137	-0.192	0.040	-0.010	0.140
		(0.094)	(0.085)	–	(0.075)	(0.044)	(0.127)	(0.062)	(0.045)	(0.057)
	Tues.	-0.242	-0.094	-0.010	0.222	–	0.078	0.009	–	–
		(0.101)	(0.085)	(0.066)	(0.080)	–	(0.117)	(0.070)	–	–
	Wed.	–	–	0.012	0.199	0.039	-0.206	0.099	0.177	0.004
		–	–	(0.064)	(0.084)	(0.048)	(0.116)	(0.070)	(0.056)	(0.052)
	Thurs.	0.301	0.124	-0.028	0.212	-0.066	–	0.183	0.188	0.092
		(0.103)	(0.082)	(0.054)	(0.072)	(0.049)	–	(0.068)	(0.053)	(0.056)
	Fri.	0.318	0.118	-0.012	0.233	-0.203	0.093	0.275	0.247	0.113
		(0.089)	(0.084)	(0.059)	(0.076)	(0.058)	(0.108)	(0.060)	(0.050)	(0.051)
	Sat.	-0.376	-0.216	-0.124	–	-0.500	-0.559	–	-0.224	-0.045
		(0.129)	(0.088)	(0.065)	–	(0.051)	(0.137)	–	(0.049)	(0.054)
	Sun.	-0.025	-0.091	0.107	0.782	-0.225	-0.479	-0.177	0.124	0.079
		(0.087)	(0.085)	(0.069)	(0.084)	(0.038)	(0.111)	(0.063)	(0.053)	(0.051)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.447	0.204	0.371	0.116	0.518	0.269	0.451	0.366	0.322
Summary										
Percent. of 0s		94.466	91.973	91.615	88.722	92.136	95.682	89.229	87.232	90.389
First stage R^2		0.742	0.749	0.752	0.817	0.752	0.828	0.781	0.756	0.773
Arrivals	A	0.641	0.667	1.479	1.088	2.710	0.268	1.854	3.757	1.775
Emp. Q	Q	0.180	0.110	0.256	0.179	0.488	0.102	0.291	0.670	0.264
		(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,3.00)	(0.00,1.00)	(0.00,2.00)	(0.00,3.00)	(0.00,2.00)
Model Q	$E[Q]$	0.178	0.109	0.257	0.174	0.494	0.100	0.288	0.678	0.265
		(0.01,0.63)	(0.01,0.37)	(0.04,0.76)	(0.02,0.60)	(0.05,1.65)	(0.00,0.47)	(0.03,0.92)	(0.15,1.77)	(0.04,0.75)
Elas	e	-0.501	-0.982	-1.178	-1.006	-0.375	-1.662	-0.544	-0.736	-0.836
		(-0.94,-0.21)	(-1.76,-0.27)	(-1.92,-0.45)	(-1.86,-0.40)	(-0.45,-0.27)	(-2.74,-0.39)	(-0.92,-0.18)	(-1.27,-0.24)	(-1.44,-0.29)
Number of Flights		976	396	753	381	1,528	711	582	823	767
Number of Dep. Dates		366	396	325	379	332	361	307	235	383
Number of Obs.		115,101	47,231	88,155	45,352	180,174	84,446	66,956	91,695	91,042

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 67: Demand Results Summary Table: Onward Connecting Traffic Instrument

Route		114	115	116	117	118	119	120	121	122
Parameter										
Leis. Price Sens.	α_L	-2.086	-2.051	-2.430	-2.217	-0.857	-0.467	-1.967	-0.416	-1.864
		(0.038)	(0.103)	(0.045)	(0.076)	(0.120)	(0.018)	(0.064)	(0.044)	(0.082)
Bus. Price Sens.	α_B	-0.719	-0.864	-0.420	-0.353	-0.507	-0.171	-0.299	-0.182	-0.237
		(0.025)	(0.070)	(0.034)	(0.055)	(0.075)	(0.016)	(0.035)	(0.029)	(0.043)
DoW Prefs	Mon.	–	0.258	0.338	0.110	-0.078	0.146	–	-0.108	-0.080
		–	(0.059)	(0.129)	(0.080)	(0.081)	(0.059)	–	(0.068)	(0.043)
	Tues.	0.020	0.198	0.301	0.193	-0.122	–	0.078	-0.018	-0.040
		(0.077)	(0.076)	(0.136)	(0.065)	(0.078)	–	(0.059)	(0.068)	(0.041)
	Wed.	0.041	0.094	0.436	0.049	-0.066	0.018	0.009	–	–
		(0.067)	(0.089)	(0.114)	(0.048)	(0.063)	(0.059)	(0.065)	–	–
	Thurs.	0.062	0.033	0.308	0.034	0.357	0.175	-0.031	0.266	0.066
		(0.073)	(0.056)	(0.106)	(0.055)	(0.066)	(0.057)	(0.050)	(0.066)	(0.043)
	Fri.	-0.110	-0.213	0.081	–	0.025	0.130	-0.116	0.018	0.017
		(0.065)	(0.080)	(0.169)	–	(0.061)	(0.055)	(0.058)	(0.061)	(0.051)
	Sat.	-0.248	-0.181	–	-0.369	–	-0.111	-0.273	-0.176	-0.046
		(0.091)	(0.080)	–	(0.060)	–	(0.063)	(0.057)	(0.064)	(0.052)
	Sun.	-0.163	–	-0.133	0.154	-0.116	0.035	-0.031	-0.017	-0.012
		(0.073)	–	(0.141)	(0.080)	(0.060)	(0.059)	(0.051)	(0.064)	(0.049)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.217	0.207	0.505	0.586	0.211	0.222	0.458	0.264	0.859
Summary										
Percent. of 0s		95.189	95.218	94.883	94.222	90.562	88.211	92.180	90.319	94.976
First stage R^2		0.648	0.712	0.707	0.758	0.729	0.627	0.745	0.795	0.562
Arrivals	A	0.674	0.680	0.527	1.070	3.194	2.617	2.369	3.522	4.566
Emp. Q	Q	0.192	0.224	0.200	0.239	0.215	0.230	0.423	0.200	0.174
		(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.194	0.225	0.199	0.241	0.222	0.233	0.427	0.207	0.194
		(0.02,0.74)	(0.02,0.88)	(0.02,0.66)	(0.03,0.80)	(0.04,0.69)	(0.04,0.74)	(0.04,1.43)	(0.04,0.63)	(0.04,0.53)
Elas	e	-2.147	-2.220	-1.025	-0.793	-1.900	-0.884	-0.813	-0.996	-1.109
		(-2.79,-1.11)	(-3.04,-1.31)	(-1.37,-0.65)	(-0.98,-0.54)	(-2.55,-1.52)	(-1.47,-0.43)	(-1.00,-0.51)	(-1.54,-0.73)	(-1.61,-0.77)
Number of Flights		1,242	1,443	687	1,314	316	452	1,298	276	671
Number of Dep. Dates		371	363	198	384	210	378	314	215	362
Number of Obs.		147,288	170,376	77,032	155,366	37,711	53,729	150,869	32,599	80,043

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 68: Demand Results Summary Table: Onward Connecting Traffic Instrument

Route		123	124	125	126	127	128	129	130	131
Parameter										
Leis. Price Sens.	α_L	-1.853	-2.348	-0.991	-1.430	-1.609	-0.489	-1.459	-1.170	-1.246
		(0.080)	(0.412)	(0.056)	(0.109)	(0.097)	(0.039)	(0.051)	(0.172)	(0.111)
Bus. Price Sens.	α_B	-0.633	-0.303	-0.138	-0.556	-0.623	-0.288	-0.259	-0.166	-0.400
		(0.029)	(0.041)	(0.028)	(0.086)	(0.053)	(0.031)	(0.032)	(0.039)	(0.075)
DoW Prefs	Mon.	-0.013	0.363	0.199	0.230	0.153	-0.281	–	0.580	0.154
		(0.057)	(0.091)	(0.095)	(0.043)	(0.089)	(0.093)	–	(0.070)	(0.075)
	Tues.	0.031	0.011	–	0.322	0.231	-0.428	-0.493	0.504	0.152
		(0.095)	(0.099)	–	(0.053)	(0.072)	(0.097)	(0.068)	(0.105)	(0.078)
	Wed.	0.080	0.201	–	0.235	0.288	-0.197	-0.558	0.073	0.129
		(0.076)	(0.090)	(0.097)	(0.052)	(0.094)	(0.083)	(0.068)	(0.078)	(0.085)
	Thurs.	–	0.321	-0.223	0.316	0.421	–	-0.350	0.325	-0.035
		–	(0.095)	(0.083)	(0.058)	(0.062)	–	(0.067)	(0.092)	(0.074)
	Fri.	-0.098	–	-0.183	0.301	0.049	-0.239	-0.694	0.282	-0.043
		(0.069)	–	(0.083)	(0.055)	(0.064)	(0.080)	(0.069)	(0.075)	(0.068)
	Sat.	-0.109	0.091	-0.305	–	–	-0.486	-0.837	–	0.035
		(0.064)	(0.084)	(0.088)	–	–	(0.087)	(0.072)	–	(0.076)
	Sun.	0.104	0.145	0.375	0.182	0.026	-0.338	0.292	0.223	–
		(0.068)	(0.091)	(0.089)	(0.050)	(0.088)	(0.086)	(0.071)	(0.085)	–
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.344	0.535	0.171	0.186	0.330	0.261	0.240	0.452	0.192
Summary										
Percent. of 0s		94.252	92.910	91.532	92.189	95.160	91.705	82.390	93.659	93.274
First stage R^2		0.677	0.834	0.785	0.742	0.741	0.779	0.800	0.713	0.652
Arrivals	A	1.367	0.824	0.668	2.803	0.681	2.082	1.560	1.024	0.784
Emp. Q	Q	0.309	0.085	0.116	0.493	0.228	0.128	0.307	0.291	0.170
		(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,3.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)
Model Q	$E[Q]$	0.314	0.085	0.114	0.503	0.231	0.130	0.297	0.290	0.168
		(0.04,1.13)	(0.02,0.23)	(0.01,0.40)	(0.06,1.68)	(0.02,0.89)	(0.01,0.41)	(0.04,1.10)	(0.04,0.87)	(0.01,0.59)
Elas	e	-1.521	-0.670	-1.033	-1.918	-1.539	-1.138	-1.692	-0.879	-1.421
		(-1.92,-1.15)	(-0.91,-0.50)	(-1.75,-0.24)	(-2.55,-1.13)	(-2.18,-0.92)	(-1.69,-0.74)	(-3.38,-0.34)	(-1.31,-0.34)	(-2.03,-0.71)
Number of Flights		1,403	371	397	1,495	1,372	196	391	790	622
Number of Dep. Dates		319	371	396	315	345	192	391	226	308
Number of Obs.		164,088	44,200	47,306	171,177	162,637	22,953	46,734	92,967	69,175

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 69: Demand Results Summary Table: Onward Connecting Traffic Instrument

Route		132	133	134	135	136	137	138	139	140
Parameter										
Leis. Price Sens.	α_L	-1.707	-2.191	-1.093	-1.546	-1.352	-3.090	-1.890	-2.936	-1.412
		(0.103)	(0.122)	(0.052)	(0.101)	(0.063)	(0.176)	(0.044)	(0.217)	(0.068)
Bus. Price Sens.	α_B	-0.547	-1.233	-0.291	-0.239	-0.108	-0.398	-0.068	-0.330	-0.198
		(0.062)	(0.119)	(0.038)	(0.040)	(0.020)	(0.039)	(0.017)	(0.036)	(0.043)
DoW Prefs	Mon.	0.078	0.453	0.162	-0.037	0.183	-0.106	-0.262	-0.205	0.241
		(0.074)	(0.092)	(0.079)	(0.073)	(0.063)	(0.083)	(0.091)	(0.077)	(0.081)
	Tues.	-0.029	0.223	0.111	-0.222	-0.092	-0.082	-0.272	0.238	–
		(0.071)	(0.104)	(0.084)	(0.082)	(0.073)	(0.104)	(0.088)	(0.142)	–
	Wed.	0.208	–	0.199	-0.245	–	–	0.344	–	-0.214
		(0.085)	–	(0.079)	(0.091)	–	–	(0.092)	–	(0.074)
	Thurs.	0.075	0.066	0.195	-0.158	0.057	0.030	1.536	0.687	0.174
		(0.078)	(0.090)	(0.081)	(0.100)	(0.068)	(0.108)	(0.120)	(0.165)	(0.077)
	Fri.	0.173	0.018	0.331	-0.194	0.011	0.199	-0.278	-0.219	0.364
		(0.078)	(0.093)	(0.079)	(0.094)	(0.066)	(0.090)	(0.082)	(0.080)	(0.076)
	Sat.	–	-0.008	–	-0.330	-0.345	-0.201	-0.437	-0.418	-0.051
		–	(0.092)	–	(0.081)	(0.074)	(0.083)	(0.122)	(0.092)	(0.078)
	Sun.	0.101	0.118	0.262	–	0.019	-0.024	–	-0.605	-0.249
		(0.085)	(0.087)	(0.080)	–	(0.079)	(0.077)	–	(0.072)	(0.074)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.373	0.214	0.242	0.809	0.451	0.370	0.319	0.418	0.282
Summary										
Percent. of 0s		92.570	90.980	89.588	91.696	90.626	95.207	83.825	92.567	83.372
First stage R^2		0.834	0.817	0.754	0.799	0.793	0.762	0.735	0.759	0.778
Arrivals	A	1.066	0.755	0.893	2.307	1.103	1.450	0.988	1.249	1.121
Emp. Q	Q	0.221	0.146	0.155	0.127	0.244	0.170	0.283	0.397	0.283
		(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.220	0.143	0.150	0.130	0.240	0.172	0.268	0.391	0.266
		(0.02,0.80)	(0.01,0.57)	(0.02,0.51)	(0.02,0.39)	(0.03,0.69)	(0.02,0.60)	(0.02,1.06)	(0.02,1.58)	(0.04,0.92)
Elas	e	-1.287	-1.981	-1.221	-0.664	-0.780	-0.868	-1.357	-1.105	-1.394
		(-1.71,-0.67)	(-2.55,-1.22)	(-2.29,-0.40)	(-1.07,-0.49)	(-1.32,-0.20)	(-1.16,-0.66)	(-3.04,-0.13)	(-1.50,-0.68)	(-2.77,-0.20)
Number of Flights		623	318	389	191	671	718	336	794	387
Number of Dep. Dates		278	299	389	188	338	267	335	193	387
Number of Obs.		73,598	37,682	46,464	22,483	76,893	82,972	39,900	90,762	46,205

Note: For the “parameter” rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the “summary” rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled “Percent. of 0s”, the r-squared of a regression of prices on the controls and instruments is in “First stage R^2”, the mean of the estimated posterior distribution for the arrivals process is in “A”, the average total number of purchases observed in the data is in “Emp. Q” with the 5th and 95th percentile of purchases in parentheses, our model’s prediction of the average total number of purchases is in “Model Q” with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled “Elas”. Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 70: Demand Results Summary Table: Additional 50% Scaling Arrivals

Route		1	2	3	4	5	6	7	8	9	10
Parameter											
Leis. Price Sens.	α_L	-0.941	-2.276	-0.401	-0.509	-2.357	-1.197	-3.140	-1.507	-2.450	-2.136
		(0.060)	(0.108)	(0.039)	(0.035)	(0.046)	(0.218)	(0.120)	(0.140)	(0.082)	(0.102)
Bus. Price Sens.	α_B	-0.216	-0.438	-0.030	-0.106	-0.089	-0.284	-1.062	-0.081	-0.546	-0.426
		(0.035)	(0.057)	(0.007)	(0.021)	(0.023)	(0.022)	(0.119)	(0.019)	(0.042)	(0.058)
DoW Prefs	Mon.	0.044	0.024	-0.168	-0.513	0.074	–	–	0.136	0.317	0.474
		(0.049)	(0.062)	(0.050)	(0.079)	(0.061)	–	–	(0.072)	(0.070)	(0.148)
	Tues.	0.020	0.194	0.187	-0.414	-0.107	-0.124	-0.070	0.061	0.310	0.257
		(0.052)	(0.056)	(0.054)	(0.086)	(0.061)	(0.064)	(0.081)	(0.076)	(0.118)	(0.117)
	Wed.	0.147	0.176	0.264	-0.134	-0.080	-0.072	-0.113	–	0.294	0.515
		(0.050)	(0.065)	(0.049)	(0.087)	(0.064)	(0.062)	(0.069)	–	(0.060)	(0.101)
	Thurs.	0.122	0.103	0.290	-0.059	-0.142	-0.058	-0.128	-0.221	0.337	0.301
		(0.045)	(0.051)	(0.050)	(0.083)	(0.065)	(0.065)	(0.067)	(0.067)	(0.069)	(0.118)
	Fri.	0.132	0.093	0.165	–	–	-0.130	-0.234	-0.072	0.216	0.172
		(0.047)	(0.051)	(0.053)	–	–	(0.065)	(0.072)	(0.068)	(0.058)	(0.102)
	Sat.	–	-0.047	-0.039	-0.039	-0.133	-0.101	-0.019	-0.255	-0.153	–
		–	(0.048)	(0.051)	(0.084)	(0.068)	(0.061)	(0.082)	(0.088)	(0.067)	–
	Sun.	0.048	–	–	-0.184	-0.017	0.275	0.001	-0.022	–	0.096
		(0.049)	–	–	(0.084)	(0.065)	(0.059)	(0.090)	(0.074)	–	(0.112)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.237	0.559	0.282	0.125	0.540	0.665	0.160	0.373	0.405	0.292
Summary											
Percent. of 0s		85.3	94.5	88.2	85.7	94.0	92.0	95.4	92.5	94.8	95.7
First stage R^2		0.828	0.690	0.614	0.730	0.820	0.771	0.868	0.777	0.655	0.587
Arrivals	A	3.697	1.525	2.828	5.334	5.846	4.364	0.922	1.047	1.330	0.532
Emp. Q	Q	0.279	0.226	0.228	0.249	0.195	0.172	0.095	0.192	0.243	0.104
		(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)
Model Q	$E[Q]$	0.283	0.230	0.233	0.258	0.214	0.181	0.097	0.191	0.246	0.104
		(0.03,1.02)	(0.02,0.78)	(0.04,0.71)	(0.08,0.78)	(0.04,0.64)	(0.03,0.55)	(0.01,0.39)	(0.02,0.69)	(0.02,0.88)	(0.01,0.35)
Elas	e	-1.211	-0.886	-0.729	-1.758	-0.306	-0.984	-1.692	-0.699	-1.311	-1.605
		(-2.03,-0.54)	(-1.11,-0.67)	(-1.14,-0.21)	(-2.66,-0.75)	(-0.47,-0.23)	(-1.34,-0.80)	(-2.01,-0.88)	(-1.04,-0.17)	(-1.56,-0.89)	(-2.24,-0.79)
Number of Flights		488	1,290	509	107	331	315	670	752	1,060	487
Number of Dep. Dates		393	379	393	107	163	203	392	387	274	238
Number of Obs.		58,076	156,777	60,721	12,791	38,847	37,319	79,955	89,486	124,843	56,307

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 71: Demand Results Summary Table: Additional 50% Scaling Arrivals

Route		11	12	13	14	15	16	17	18	19	20
Parameter											
Leis. Price Sens.	α_L	-3.042	-0.410	-2.092	-0.440	-1.756	-1.369	-2.420	-2.556	-2.716	-1.925
		(0.109)	(0.036)	(0.249)	(0.042)	(0.223)	(0.128)	(0.191)	(0.152)	(0.025)	(0.361)
Bus. Price Sens.	α_B	-0.190	-0.216	-0.209	-0.111	-0.304	-0.329	-0.151	-0.591	-0.221	-0.121
		(0.037)	(0.028)	(0.038)	(0.022)	(0.033)	(0.068)	(0.023)	(0.087)	(0.028)	(0.022)
DoW Prefs	Mon.	0.117	0.263	0.081	0.146	–	–	–	0.258	0.163	–
		(0.043)	(0.071)	(0.122)	(0.053)	–	–	–	(0.072)	(0.025)	–
	Tues.	0.184	-0.086	0.016	-0.064	-0.237	0.041	-0.052	0.213	0.135	-0.122
		(0.049)	(0.065)	(0.124)	(0.054)	(0.094)	(0.070)	(0.068)	(0.075)	(0.045)	(0.079)
	Wed.	0.101	0.047	-0.026	-0.060	-0.350	-0.044	-0.169	0.106	0.095	-0.155
		(0.043)	(0.065)	(0.108)	(0.056)	(0.090)	(0.070)	(0.067)	(0.080)	(0.034)	(0.074)
	Thurs.	0.021	–	-0.147	-0.021	-0.337	-0.044	-0.232	–	–	-0.252
		(0.054)	–	(0.112)	(0.057)	(0.075)	(0.065)	(0.061)	–	–	(0.073)
	Fri.	–	0.008	–	–	-0.350	-0.111	-0.360	-0.098	-0.146	-0.396
		–	(0.066)	–	–	(0.086)	(0.057)	(0.061)	(0.061)	(0.027)	(0.072)
	Sat.	-0.137	0.262	-0.235	-0.222	-0.256	-0.371	-0.294	-0.079	-0.122	-0.324
		(0.050)	(0.073)	(0.102)	(0.053)	(0.080)	(0.054)	(0.063)	(0.081)	(0.034)	(0.074)
	Sun.	-0.021	0.646	-0.067	0.125	-0.443	-0.306	-0.303	0.430	-0.224	-0.294
		(0.053)	(0.084)	(0.094)	(0.055)	(0.076)	(0.055)	(0.058)	(0.102)	(0.031)	(0.077)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.529	0.213	0.497	0.313	0.355	0.258	0.508	0.207	0.420	0.613
Summary											
Percent. of 0s		90.9	84.5	94.3	88.4	90.7	91.8	90.1	93.0	87.0	91.2
First stage R^2		0.849	0.760	0.798	0.649	0.798	0.653	0.617	0.611	0.827	0.601
Arrivals	A	2.708	4.502	3.687	3.260	1.268	1.326	1.658	1.504	8.557	1.471
Emp. Q	Q	0.571	0.288	0.099	0.225	0.128	0.302	0.249	0.097	1.195	0.118
		(0.00,3.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,6.00)	(0.00,1.00)
Model Q	$E[Q]$	0.575	0.295	0.106	0.230	0.129	0.302	0.250	0.098	1.211	0.119
		(0.04,2.17)	(0.09,1.01)	(0.02,0.28)	(0.04,0.73)	(0.01,0.47)	(0.02,1.06)	(0.02,0.88)	(0.01,0.35)	(0.11,4.33)	(0.02,0.35)
Elas	e	-0.438	-1.179	-0.731	-0.728	-1.064	-1.635	-0.517	-1.322	-0.637	-0.371
		(-0.60,-0.22)	(-2.04,-0.56)	(-1.48,-0.53)	(-1.24,-0.36)	(-1.66,-0.39)	(-2.43,-0.66)	(-0.73,-0.23)	(-2.04,-0.56)	(-0.82,-0.39)	(-0.56,-0.18)
Number of Flights		1,453	217	123	444	304	960	647	335	1,712	391
Number of Dep. Dates		315	217	103	372	304	343	351	335	285	371
Number of Obs.		170,795	25,825	13,448	52,716	35,746	110,780	76,854	40,059	200,018	44,405

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 72: Demand Results Summary Table: Additional 50% Scaling Arrivals

Route		21	22	23	24	25	26	27	28	29	30
Parameter											
Leis. Price Sens.	α_L	-1.741	-1.548	-2.963	-1.696	-2.251	-1.095	-2.094	-0.929	-1.230	-2.151
		(0.083)	(0.196)	(0.164)	(0.224)	(0.075)	(0.103)	(0.050)	(0.130)	(0.104)	(0.078)
Bus. Price Sens.	α_B	-0.244	-0.020	-1.226	-0.128	-0.605	-0.155	-0.365	-0.183	-0.287	-0.105
		(0.052)	(0.004)	(0.142)	(0.029)	(0.028)	(0.051)	(0.050)	(0.043)	(0.032)	(0.019)
DoW Prefs	Mon.	0.220	–	-0.149	–	0.691	-0.227	–	0.088	-0.052	0.099
		(0.088)	–	(0.084)	–	(0.095)	(0.080)	–	(0.049)	(0.052)	(0.047)
	Tues.	-0.051	-0.180	–	-0.066	0.491	-0.252	-0.028	-0.086	-0.125	0.022
		(0.095)	(0.052)	–	(0.069)	(0.081)	(0.081)	(0.057)	(0.052)	(0.056)	(0.053)
	Wed.	-0.056	-0.274	0.027	-0.084	0.260	-0.127	0.084	-0.055	-0.003	0.128
		(0.096)	(0.049)	(0.092)	(0.073)	(0.067)	(0.080)	(0.057)	(0.050)	(0.063)	(0.051)
	Thurs.	0.075	-0.347	-0.089	-0.331	0.059	–	-0.079	-0.030	-0.015	0.085
		(0.096)	(0.050)	(0.086)	(0.079)	(0.065)	–	(0.047)	(0.044)	(0.051)	(0.047)
	Fri.	–	-0.418	-0.096	-0.253	-0.030	-0.130	-0.305	–	-0.115	–
		–	(0.049)	(0.074)	(0.075)	(0.075)	(0.079)	(0.051)	–	(0.052)	–
	Sat.	0.075	-0.398	0.162	-0.407	–	-0.262	-0.247	-0.072	-0.000	-0.333
		(0.112)	(0.053)	(0.087)	(0.087)	–	(0.080)	(0.059)	(0.044)	(0.058)	(0.052)
	Sun.	-0.055	0.006	0.547	-0.111	0.412	0.221	-0.022	0.292	–	-0.082
		(0.096)	(0.051)	(0.074)	(0.071)	(0.084)	(0.082)	(0.060)	(0.051)	–	(0.044)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.329	0.671	0.145	0.397	0.372	0.361	0.447	0.405	0.374	0.700
Summary											
Percent. of 0s		90.4	88.6	95.5	92.2	94.8	90.9	92.9	90.3	92.9	92.5
First stage R^2		0.691	0.632	0.880	0.780	0.705	0.612	0.728	0.748	0.781	0.844
Arrivals	A	0.894	2.777	0.855	1.017	1.380	1.448	2.696	2.410	2.312	2.792
Emp. Q	Q	0.134	0.222	0.093	0.198	0.242	0.120	0.549	0.315	0.307	0.332
		(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,3.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.134	0.224	0.095	0.196	0.246	0.121	0.554	0.320	0.314	0.340
		(0.01,0.52)	(0.04,0.67)	(0.01,0.39)	(0.02,0.68)	(0.02,0.88)	(0.02,0.36)	(0.04,2.19)	(0.04,0.93)	(0.05,0.91)	(0.05,1.03)
Elas	e	-1.269	-0.110	-1.719	-0.710	-1.592	-0.825	-0.927	-0.854	-1.081	-0.262
		(-1.95,-0.37)	(-0.15,-0.06)	(-2.00,-0.88)	(-1.03,-0.26)	(-1.94,-1.00)	(-1.32,-0.34)	(-1.18,-0.57)	(-1.22,-0.43)	(-1.40,-0.59)	(-0.41,-0.19)
Number of Flights		259	517	671	752	1,152	364	1,660	792	983	1,004
Number of Dep. Dates		258	394	393	387	298	347	279	322	307	308
Number of Obs.		30,531	61,710	80,066	89,341	135,404	41,459	195,980	91,287	116,084	118,320

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 73: Demand Results Summary Table: Additional 50% Scaling Arrivals

Route		31	32	33	34	35	36	37	38	39	40
Parameter											
Leis. Price Sens.	α_L	-3.054	-0.902	-0.849	-0.971	-2.240	-2.050	-2.522	-1.057	-2.293	-1.702
		(0.049)	(0.081)	(0.070)	(0.018)	(0.050)	(0.177)	(0.201)	(0.087)	(0.054)	(0.144)
Bus. Price Sens.	α_B	-0.281	-0.246	-0.212	-0.027	-0.283	-0.108	-0.635	-0.264	-0.269	-0.528
		(0.020)	(0.044)	(0.027)	(0.006)	(0.038)	(0.020)	(0.149)	(0.030)	(0.019)	(0.066)
DoW Prefs	Mon.	0.180	–	-0.037	-0.116	–	-0.017	0.137	0.113	–	-0.075
		(0.082)	–	(0.056)	(0.047)	–	(0.060)	(0.111)	(0.049)	–	(0.071)
	Tues.	-0.010	-0.224	-0.231	-0.180	-0.180	–	0.113	-0.061	0.024	-0.006
		(0.089)	(0.060)	(0.059)	(0.047)	(0.061)	–	(0.119)	(0.052)	(0.055)	(0.095)
	Wed.	–	-0.350	-0.169	–	-0.232	0.004	–	–	-0.026	0.082
		–	(0.060)	(0.058)	–	(0.113)	(0.063)	–	–	(0.078)	(0.072)
	Thurs.	-0.170	-0.260	-0.179	0.079	-0.422	-0.009	-0.195	-0.059	-0.078	-0.002
		(0.076)	(0.059)	(0.053)	(0.047)	(0.072)	(0.057)	(0.095)	(0.047)	(0.063)	(0.064)
	Fri.	-0.600	-0.351	-0.219	0.205	-0.426	-0.017	-0.199	-0.063	-0.170	–
		(0.077)	(0.053)	(0.054)	(0.046)	(0.096)	(0.053)	(0.099)	(0.045)	(0.084)	–
	Sat.	-0.501	-0.446	-0.247	0.785	-0.603	-0.060	-0.163	-0.186	-0.421	-0.103
		(0.069)	(0.059)	(0.056)	(0.051)	(0.091)	(0.070)	(0.107)	(0.048)	(0.062)	(0.081)
	Sun.	-0.175	0.020	–	0.321	-0.052	0.115	0.175	0.217	-0.091	0.108
		(0.059)	(0.060)	–	(0.048)	(0.095)	(0.061)	(0.092)	(0.049)	(0.060)	(0.072)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.537	0.233	0.452	0.011	0.423	0.583	0.178	0.438	0.450	0.375
Summary											
Percent. of 0s		94.3	92.1	91.1	86.5	94.5	91.8	95.7	90.6	94.0	92.3
First stage R^2		0.682	0.721	0.746	0.654	0.739	0.740	0.736	0.764	0.720	0.846
Arrivals	A	1.018	1.725	1.753	10.180	0.901	2.265	0.408	2.672	1.490	1.566
Emp. Q	Q	0.194	0.282	0.225	0.300	0.181	0.255	0.101	0.255	0.250	0.232
		(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.196	0.287	0.228	0.327	0.181	0.259	0.102	0.259	0.253	0.234
		(0.01,0.70)	(0.04,0.88)	(0.03,0.69)	(0.07,1.11)	(0.02,0.62)	(0.04,0.77)	(0.00,0.48)	(0.04,0.72)	(0.03,0.80)	(0.02,0.85)
Elas	e	-0.547	-1.202	-0.851	-3.057	-0.823	-0.335	-2.005	-1.031	-0.734	-1.314
		(-0.77,-0.39)	(-1.88,-0.59)	(-1.24,-0.37)	(-4.80,-0.55)	(-1.12,-0.50)	(-0.51,-0.19)	(-3.35,-0.56)	(-1.48,-0.52)	(-0.91,-0.51)	(-1.86,-0.64)
Number of Flights		807	836	713	394	941	729	721	772	952	516
Number of Dep. Dates		276	309	373	389	354	311	365	386	279	221
Number of Obs.		95,441	98,207	84,575	47,069	111,049	85,158	85,695	91,643	110,327	58,546

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 74: Demand Results Summary Table: Additional 50% Scaling Arrivals

Route		41	42	43	44	45	46	47	48	49	50
Parameter											
Leis. Price Sens.	α_L	-0.972	-2.945	-0.906	-2.380	-1.828	-0.585	-1.180	-2.424	-3.714	-1.345
		(0.059)	(0.044)	(0.062)	(0.122)	(0.056)	(0.212)	(0.070)	(0.111)	(0.213)	(0.040)
Bus. Price Sens.	α_B	-0.210	-0.168	-0.141	-0.222	-0.339	-0.147	-0.176	-0.509	-0.103	-0.065
		(0.035)	(0.050)	(0.026)	(0.031)	(0.032)	(0.026)	(0.025)	(0.020)	(0.025)	(0.013)
DoW Prefs	Mon.	0.247	-0.034	-0.057	0.074	0.153	-0.061	-0.126	-0.124	-0.181	1.928
		(0.071)	(0.037)	(0.045)	(0.037)	(0.056)	(0.062)	(0.071)	(0.027)	(0.082)	(0.107)
	Tues.	0.020	0.034	-0.107	0.199	0.177	-0.277	-0.135	-0.084	–	0.580
		(0.074)	(0.038)	(0.046)	(0.037)	(0.054)	(0.065)	(0.076)	(0.035)	–	(0.077)
	Wed.	0.124	0.037	-0.052	0.212	0.190	-0.171	-0.009	0.082	0.060	0.215
		(0.074)	(0.048)	(0.050)	(0.041)	(0.052)	(0.060)	(0.078)	(0.028)	(0.109)	(0.072)
	Thurs.	-0.015	0.050	0.025	0.094	0.140	0.041	0.057	0.189	-0.011	-0.040
		(0.067)	(0.041)	(0.045)	(0.042)	(0.045)	(0.059)	(0.066)	(0.028)	(0.083)	(0.071)
	Fri.	–	-0.132	-0.033	-0.052	0.229	–	-0.088	-0.021	-0.321	–
		–	(0.033)	(0.050)	(0.035)	(0.045)	–	(0.068)	(0.035)	(0.067)	–
	Sat.	-0.164	-0.182	-0.132	-0.162	–	0.039	–	-0.093	-0.475	-0.169
		(0.069)	(0.037)	(0.053)	(0.038)	–	(0.060)	–	(0.033)	(0.097)	(0.105)
	Sun.	0.346	–	–	–	0.164	-0.149	-0.006	–	-0.317	-0.185
		(0.073)	–	–	–	(0.047)	(0.059)	(0.067)	–	(0.094)	(0.074)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.332	0.538	0.293	0.442	0.406	0.892	0.418	0.345	0.531	0.260
Summary											
Percent. of 0s		88.6	92.9	90.4	92.2	90.8	84.3	90.3	86.3	90.6	83.4
First stage R^2		0.775	0.741	0.793	0.735	0.853	0.733	0.630	0.786	0.776	0.800
Arrivals	A	1.337	2.700	2.377	3.322	2.768	5.309	1.584	8.414	1.176	1.445
Emp. Q	Q	0.170	0.553	0.302	0.419	0.578	0.310	0.244	1.238	0.330	0.316
		(0.00,1.00)	(0.00,3.00)	(0.00,2.00)	(0.00,2.00)	(0.00,3.00)	(0.00,2.00)	(0.00,2.00)	(0.00,6.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.169	0.556	0.307	0.425	0.585	0.319	0.245	1.253	0.330	0.303
		(0.02,0.58)	(0.02,2.18)	(0.04,0.90)	(0.04,1.45)	(0.04,2.26)	(0.08,1.11)	(0.02,0.87)	(0.12,4.44)	(0.01,1.45)	(0.02,1.28)
Elas	e	-0.984	-0.381	-0.961	-0.587	-0.842	-0.532	-0.666	-1.348	-0.281	-1.366
		(-1.75,-0.31)	(-0.56,-0.24)	(-1.48,-0.36)	(-0.68,-0.42)	(-1.14,-0.42)	(-0.78,-0.26)	(-1.12,-0.27)	(-1.68,-0.85)	(-0.57,-0.12)	(-3.45,-0.13)
Number of Flights		390	1,641	876	1,462	1,387	221	659	1,703	559	333
Number of Dep. Dates		390	276	375	359	301	221	355	284	214	333
Number of Obs.		46,582	194,693	103,754	173,340	162,964	26,363	77,914	204,289	66,438	39,701

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 75: Demand Results Summary Table: Additional 50% Scaling Arrivals

Route		51	52	53	54	55	56	57	58	59
Parameter										
Leis. Price Sens.	α_L	-2.728	-1.637	-0.281	-1.573	-2.148	-0.948	-1.381	-1.556	-2.043
		(0.093)	(0.235)	(0.015)	(0.408)	(0.085)	(0.137)	(0.174)	(0.104)	(0.041)
Bus. Price Sens.	α_B	-0.314	-0.252	-0.089	-0.072	-0.169	-0.245	-0.171	-0.233	-0.694
		(0.032)	(0.028)	(0.012)	(0.018)	(0.036)	(0.035)	(0.048)	(0.041)	(0.047)
DoW Prefs	Mon.	-0.259	0.005	-0.246	0.022	–	0.099	0.252	0.186	0.416
		(0.074)	(0.107)	(0.042)	(0.080)	–	(0.102)	(0.087)	(0.100)	(0.077)
	Tues.	–	-0.114	-0.190	0.175	-0.018	-0.029	0.007	-0.066	0.501
		–	(0.111)	(0.040)	(0.088)	(0.063)	(0.101)	(0.077)	(0.097)	(0.080)
	Wed.	0.198	0.076	-0.206	0.087	0.021	0.193	-0.068	–	0.387
		(0.088)	(0.106)	(0.043)	(0.087)	(0.061)	(0.097)	(0.078)	–	(0.117)
	Thurs.	-0.013	-0.043	-0.158	-0.118	0.167	0.238	–	0.106	0.210
		(0.081)	(0.106)	(0.041)	(0.082)	(0.056)	(0.092)	–	(0.093)	(0.070)
	Fri.	-0.139	-0.134	-0.057	–	0.021	0.086	-0.276	-0.020	–
		(0.077)	(0.110)	(0.039)	–	(0.057)	(0.090)	(0.073)	(0.097)	–
	Sat.	-0.319	-0.124	–	-0.160	0.011	-0.052	-0.280	-0.068	-0.028
		(0.117)	(0.094)	–	(0.083)	(0.062)	(0.087)	(0.081)	(0.121)	(0.080)
	Sun.	-0.392	–	-0.080	0.380	0.029	–	0.325	0.417	0.170
		(0.094)	–	(0.039)	(0.082)	(0.068)	–	(0.078)	(0.101)	(0.071)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.359	0.706	0.261	0.605	0.552	0.587	0.378	0.336	0.259
Summary										
Percent. of 0s		95.4	93.0	81.3	85.1	93.8	93.6	89.8	89.9	95.3
First stage R^2		0.751	0.809	0.669	0.569	0.763	0.763	0.794	0.740	0.708
Arrivals	A	0.894	4.661	9.565	5.814	7.180	4.046	1.250	0.861	0.977
Emp. Q	Q	0.164	0.115	0.369	0.262	0.193	0.115	0.143	0.142	0.166
		(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)
Model Q	$E[Q]$	0.165	0.125	0.384	0.267	0.214	0.125	0.144	0.142	0.168
		(0.01,0.72)	(0.02,0.32)	(0.13,1.23)	(0.08,0.79)	(0.04,0.67)	(0.03,0.32)	(0.01,0.53)	(0.01,0.57)	(0.01,0.72)
Elas	e	-0.792	-0.773	-0.942	-0.339	-0.552	-0.968	-0.888	-1.273	-1.930
		(-1.02,-0.54)	(-1.23,-0.54)	(-1.39,-0.65)	(-0.48,-0.28)	(-0.87,-0.40)	(-1.39,-0.66)	(-1.57,-0.22)	(-2.10,-0.35)	(-2.46,-1.17)
Number of Flights		854	96	396	107	374	145	311	260	927
Number of Dep. Dates		291	96	396	107	194	117	311	260	317
Number of Obs.		100,922	11,463	47,336	12,774	44,311	15,440	36,570	30,454	109,772

Note: For the “parameter” rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the “summary” rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled “Percent. of 0s”, the r-squared of a regression of prices on the controls and instruments is in “First stage R^2”, the mean of the estimated posterior distribution for the arrivals process is in “A”, the average total number of purchases observed in the data is in “Emp. Q” with the 5th and 95th percentile of purchases in parentheses, our model’s prediction of the average total number of purchases is in “Model Q” with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled “Elas”. Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 76: Demand Results Summary Table: Additional 50% Scaling Arrivals

Route		60	61	62	63	64	65	66	67	68
Parameter										
Leis. Price Sens.	α_L	-2.140	-2.525	-1.797	-1.253	-1.109	-2.832	-2.348	-1.743	-1.742
		(0.212)	(0.313)	(0.052)	(0.090)	(0.084)	(0.092)	(0.091)	(0.085)	(0.143)
Bus. Price Sens.	α_B	-0.313	-0.427	-0.692	-0.249	-0.191	-0.523	-0.350	-0.257	-0.247
		(0.040)	(0.038)	(0.028)	(0.042)	(0.037)	(0.029)	(0.044)	(0.028)	(0.027)
DoW Prefs	Mon.	–	-0.364	0.109	–	-0.037	0.552	-0.007	0.602	-0.311
		–	(0.169)	(0.063)	–	(0.089)	(0.090)	(0.084)	(0.118)	(0.072)
	Tues.	-0.201	-0.695	0.170	-0.113	-0.131	0.313	–	0.507	-0.297
		(0.104)	(0.154)	(0.062)	(0.092)	(0.111)	(0.087)	–	(0.101)	(0.076)
	Wed.	0.168	–	0.030	0.049	–	0.474	-0.192	0.445	–
		(0.099)	–	(0.061)	(0.088)	–	(0.100)	(0.115)	(0.098)	–
	Thurs.	-0.083	0.033	-0.192	0.027	0.233	0.239	-0.284	0.102	-0.035
		(0.100)	(0.148)	(0.066)	(0.083)	(0.077)	(0.078)	(0.096)	(0.103)	(0.070)
	Fri.	0.062	-0.198	-0.617	-0.201	-0.397	–	-0.631	-0.093	-0.184
		(0.101)	(0.156)	(0.052)	(0.078)	(0.080)	–	(0.086)	(0.081)	(0.073)
	Sat.	-0.030	-0.131	-0.508	-0.298	-0.078	-0.233	-0.377	–	-0.297
		(0.100)	(0.123)	(0.063)	(0.087)	(0.109)	(0.086)	(0.131)	–	(0.075)
	Sun.	-0.189	-0.352	–	0.321	-0.019	0.281	0.160	0.464	-0.134
		(0.095)	(0.128)	–	(0.087)	(0.148)	(0.073)	(0.104)	(0.102)	(0.074)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.821	0.880	0.221	0.316	0.510	0.451	0.300	0.370	0.756
Summary										
Percent. of 0s		93.4	93.1	92.5	90.1	96.4	96.1	96.3	94.2	93.0
First stage R^2		0.726	0.686	0.703	0.799	0.736	0.700	0.623	0.695	0.780
Arrivals	A	4.569	6.883	1.822	1.309	0.572	0.504	0.381	1.314	5.243
Emp. Q	Q	0.117	0.142	0.474	0.136	0.230	0.130	0.096	0.340	0.119
		(0.00,1.00)	(0.00,1.00)	(0.00,3.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)
Model Q	$E[Q]$	0.127	0.161	0.474	0.137	0.228	0.130	0.096	0.339	0.129
		(0.02,0.35)	(0.03,0.40)	(0.02,2.12)	(0.01,0.50)	(0.00,1.07)	(0.00,0.64)	(0.00,0.50)	(0.02,1.44)	(0.03,0.32)
Elas	e	-0.809	-1.357	-1.942	-0.969	-0.821	-1.031	-1.186	-1.085	-0.750
		(-1.23,-0.57)	(-2.87,-0.85)	(-2.81,-1.08)	(-1.54,-0.42)	(-1.99,-0.21)	(-1.53,-0.71)	(-1.75,-0.52)	(-1.66,-0.48)	(-1.24,-0.45)
Number of Flights		117	53	1,120	283	709	965	671	602	211
Number of Dep. Dates		117	53	236	277	131	351	302	133	205
Number of Obs.		13,960	6,342	129,887	32,711	83,245	114,462	79,617	70,103	25,005

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 77: Demand Results Summary Table: Additional 50% Scaling Arrivals

Route		69	70	71	72	73	74	75	76	77
Parameter										
Leis. Price Sens.	α_L	-1.226	-1.101	-2.623	-2.509	-1.288	-2.358	-1.409	-1.815	-1.397
		(0.080)	(0.094)	(0.152)	(0.092)	(0.053)	(0.136)	(0.294)	(0.190)	(0.059)
Bus. Price Sens.	α_B	-0.072	-0.359	-0.299	-0.473	-0.065	-0.065	-0.259	-0.136	-0.215
		(0.015)	(0.052)	(0.039)	(0.020)	(0.015)	(0.016)	(0.026)	(0.020)	(0.039)
DoW Prefs	Mon.	0.283	0.028	-0.027	–	-0.167	0.134	-0.371	-0.001	-0.049
		(0.056)	(0.068)	(0.096)	–	(0.060)	(0.048)	(0.178)	(0.063)	(0.056)
	Tues.	0.139	0.181	–	-0.257	-0.131	-0.036	-0.382	-0.150	0.148
		(0.053)	(0.069)	–	(0.052)	(0.063)	(0.046)	(0.186)	(0.066)	(0.074)
	Wed.	–	0.155	-0.060	-0.310	-0.174	0.061	0.253	-0.158	0.089
		–	(0.063)	(0.088)	(0.085)	(0.089)	(0.055)	(0.157)	(0.065)	(0.071)
	Thurs.	-0.049	0.044	-0.049	-0.602	-0.120	–	-0.017	-0.163	–
		(0.049)	(0.058)	(0.083)	(0.073)	(0.060)	–	(0.170)	(0.064)	–
	Fri.	-0.251	–	-0.176	-0.927	–	0.080	-0.188	-0.153	-0.142
		(0.047)	–	(0.083)	(0.054)	–	(0.054)	(0.158)	(0.062)	(0.070)
	Sat.	-0.240	0.021	-0.392	-0.775	0.275	-0.152	–	-0.261	-0.334
		(0.051)	(0.070)	(0.102)	(0.066)	(0.059)	(0.062)	–	(0.070)	(0.055)
	Sun.	0.295	0.343	-0.042	-0.233	-0.170	0.046	-0.167	–	-0.437
		(0.057)	(0.070)	(0.074)	(0.080)	(0.084)	(0.054)	(0.103)	–	(0.068)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.404	0.191	0.275	0.356	0.041	0.735	0.925	0.926	0.326
Summary										
Percent. of 0s		88.8	93.0	95.1	92.4	78.8	92.5	91.8	90.8	92.7
First stage R^2		0.788	0.655	0.735	0.745	0.437	0.830	0.789	0.780	0.670
Arrivals	A	3.082	1.278	2.513	1.944	4.185	2.696	4.921	4.504	1.683
Emp. Q	Q	0.319	0.180	0.179	0.394	0.402	0.339	0.149	0.188	0.461
		(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,3.00)
Model Q	$E[Q]$	0.322	0.182	0.183	0.395	0.407	0.347	0.162	0.198	0.459
		(0.04,1.02)	(0.01,0.64)	(0.02,0.68)	(0.02,1.62)	(0.03,1.52)	(0.06,1.05)	(0.04,0.42)	(0.04,0.60)	(0.02,2.13)
Elas	e	-0.655	-1.448	-0.811	-1.271	-2.502	-0.174	-1.036	-0.450	-1.017
		(-1.01,-0.15)	(-1.97,-0.78)	(-0.95,-0.64)	(-1.63,-0.73)	(-3.88,-1.31)	(-0.26,-0.11)	(-1.76,-0.66)	(-0.61,-0.35)	(-1.39,-0.35)
Number of Flights		597	636	630	898	301	1,011	51	266	966
Number of Dep. Dates		303	313	226	230	301	307	51	208	204
Number of Obs.		68,698	70,651	71,472	104,037	35,989	118,859	6,086	31,374	111,843

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 78: Demand Results Summary Table: Additional 50% Scaling Arrivals

Route		78	79	80	81	82	83	84	85	86
Parameter										
Leis. Price Sens.	α_L	-1.074	-1.097	-0.562	-0.860	-1.804	-1.511	-1.713	-1.367	-0.867
		(0.071)	(0.046)	(0.045)	(0.059)	(0.082)	(0.170)	(0.142)	(0.043)	(0.135)
Bus. Price Sens.	α_B	-0.295	-0.067	-0.083	-0.187	-0.539	-0.709	-0.258	-0.315	-0.450
		(0.028)	(0.021)	(0.018)	(0.031)	(0.032)	(0.117)	(0.060)	(0.033)	(0.087)
DoW Prefs	Mon.	0.140	-0.083	0.035	-0.098	-0.115	–	–	0.354	-0.030
		(0.047)	(0.055)	(0.034)	(0.076)	(0.073)	–	–	(0.131)	(0.050)
	Tues.	0.016	-0.080	0.191	–	-0.066	0.116	-0.226	-0.173	0.001
		(0.053)	(0.055)	(0.039)	–	(0.062)	(0.091)	(0.097)	(0.134)	(0.046)
	Wed.	-0.023	-0.331	0.184	0.097	-0.015	0.140	-0.265	-0.367	–
		(0.047)	(0.085)	(0.038)	(0.076)	(0.055)	(0.089)	(0.092)	(0.099)	–
	Thurs.	0.012	-0.028	0.068	-0.003	–	0.348	-0.376	-0.057	-0.024
		(0.046)	(0.055)	(0.034)	(0.067)	–	(0.080)	(0.089)	(0.116)	(0.045)
	Fri.	-0.007	–	-0.111	-0.054	-0.023	0.342	-0.226	-0.325	0.486
		(0.044)	–	(0.032)	(0.066)	(0.060)	(0.089)	(0.085)	(0.110)	(0.097)
	Sat.	–	0.171	-0.173	-0.359	-0.349	-0.168	-0.312	-0.569	0.665
		–	(0.064)	(0.033)	(0.075)	(0.062)	(0.093)	(0.091)	(0.118)	(0.124)
	Sun.	0.239	-0.025	–	0.174	-0.125	0.028	-0.341	–	0.486
		(0.047)	(0.081)	–	(0.069)	(0.055)	(0.086)	(0.089)	–	(0.102)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.217	0.049	0.255	0.178	0.188	0.234	0.414	0.447	0.099
Summary										
Percent. of 0s		84.6	77.4	88.9	89.5	95.2	90.4	90.9	96.6	95.0
First stage R^2		0.825	0.443	0.743	0.830	0.664	0.891	0.756	0.746	0.643
Arrivals	A	3.755	4.383	3.561	1.586	0.978	1.160	1.223	0.553	5.905
Emp. Q	Q	0.293	0.441	0.642	0.165	0.189	0.154	0.124	0.222	0.168
		(0.00,2.00)	(0.00,3.00)	(0.00,3.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.298	0.447	0.648	0.164	0.192	0.154	0.125	0.222	0.192
		(0.04,1.06)	(0.04,1.68)	(0.06,2.42)	(0.02,0.56)	(0.02,0.72)	(0.01,0.62)	(0.01,0.43)	(0.01,1.08)	(0.05,0.51)
Elas	e	-1.248	-2.226	-0.520	-0.963	-1.848	-1.228	-0.848	-1.075	-3.328
		(-1.96,-0.65)	(-3.56,-1.15)	(-0.82,-0.17)	(-1.71,-0.41)	(-2.33,-0.90)	(-1.67,-0.71)	(-1.21,-0.42)	(-2.19,-0.36)	(-4.11,-2.38)
Number of Flights		489	301	1,371	391	1,219	310	282	679	632
Number of Dep. Dates		394	301	346	385	366	291	275	125	345
Number of Obs.		58,278	35,965	161,536	46,185	144,519	36,602	32,588	79,820	75,464

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 79: Demand Results Summary Table: Additional 50% Scaling Arrivals

Route		87	88	89	90	91	92	93	94	95
Parameter										
Leis. Price Sens.	α_L	-2.693	-1.098	-2.260	-3.575	-2.427	-2.617	-1.876	-0.913	-1.617
		(0.064)	(0.050)	(0.113)	(0.131)	(0.239)	(0.103)	(0.068)	(0.131)	(0.108)
Bus. Price Sens.	α_B	-0.219	-0.254	-0.428	-0.418	-0.314	-0.224	-0.129	-0.190	-0.226
		(0.030)	(0.029)	(0.035)	(0.033)	(0.054)	(0.025)	(0.018)	(0.020)	(0.025)
DoW Prefs	Mon.	-0.260	–	0.114	0.502	-0.117	0.199	-0.108	0.151	–
		(0.075)	–	(0.050)	(0.150)	(0.100)	(0.090)	(0.043)	(0.071)	–
	Tues.	0.036	-0.038	0.122	0.246	0.406	–	-0.039	-0.087	0.015
		(0.079)	(0.062)	(0.049)	(0.134)	(0.158)	–	(0.047)	(0.070)	(0.101)
	Wed.	0.056	-0.030	0.193	0.384	0.494	0.152	–	0.035	-0.203
		(0.090)	(0.063)	(0.042)	(0.166)	(0.116)	(0.104)	–	(0.077)	(0.083)
	Thurs.	–	0.115	0.029	0.306	0.366	-0.148	-0.140	0.008	-0.117
		–	(0.059)	(0.051)	(0.126)	(0.143)	(0.101)	(0.052)	(0.076)	(0.104)
	Fri.	-0.233	0.001	–	-0.127	0.260	-0.002	-0.283	–	-0.224
		(0.078)	(0.065)	–	(0.114)	(0.103)	(0.100)	(0.042)	–	(0.106)
	Sat.	-0.411	-0.105	-0.053	0.023	-0.095	-0.301	-0.271	0.167	-0.539
		(0.086)	(0.062)	(0.059)	(0.158)	(0.079)	(0.095)	(0.048)	(0.076)	(0.119)
	Sun.	-0.595	0.072	0.062	–	–	-0.177	-0.194	0.412	0.036
		(0.067)	(0.056)	(0.043)	–	–	(0.102)	(0.047)	(0.078)	(0.093)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.515	0.225	0.297	0.339	0.363	0.332	0.713	0.625	0.371
Summary										
Percent. of 0s		94.6	92.5	94.4	96.2	94.3	93.7	89.8	93.1	95.4
First stage R^2		0.612	0.722	0.685	0.632	0.647	0.730	0.769	0.805	0.621
Arrivals	A	0.992	1.736	1.968	0.375	1.271	0.782	3.350	4.333	0.540
Emp. Q	Q	0.187	0.266	0.297	0.098	0.333	0.156	0.554	0.117	0.112
		(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,3.00)	(0.00,1.00)	(0.00,1.00)
Model Q	$E[Q]$	0.187	0.269	0.301	0.098	0.331	0.155	0.559	0.125	0.111
		(0.01,0.69)	(0.03,0.84)	(0.03,1.14)	(0.00,0.50)	(0.01,1.45)	(0.01,0.61)	(0.05,2.07)	(0.03,0.31)	(0.01,0.37)
Elas	e	-0.501	-1.310	-1.196	-0.879	-1.024	-0.775	-0.294	-0.733	-1.029
		(-0.66,-0.33)	(-2.04,-0.62)	(-1.40,-0.86)	(-1.18,-0.53)	(-1.50,-0.55)	(-1.30,-0.38)	(-0.36,-0.18)	(-1.08,-0.50)	(-1.48,-0.47)
Number of Flights		846	751	1,546	595	574	621	1,403	209	478
Number of Dep. Dates		290	267	358	278	129	306	355	203	232
Number of Obs.		100,155	83,444	181,578	70,797	67,011	72,946	163,706	24,674	54,815

Note: For the “parameter” rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the “summary” rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled “Percent. of 0s”, the r-squared of a regression of prices on the controls and instruments is in “First stage R^2”, the mean of the estimated posterior distribution for the arrivals process is in “A”, the average total number of purchases observed in the data is in “Emp. Q” with the 5th and 95th percentile of purchases in parentheses, our model’s prediction of the average total number of purchases is in “Model Q” with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled “Elas”. Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 80: Demand Results Summary Table: Additional 50% Scaling Arrivals

Route		96	97	98	99	100	101	102	103	104
Parameter										
Leis. Price Sens.	α_L	-0.962	-1.363	-2.379	-2.966	-0.737	-2.638	-0.433	-0.790	-2.223
		(0.048)	(0.182)	(0.099)	(0.128)	(0.130)	(0.316)	(0.064)	(0.073)	(0.127)
Bus. Price Sens.	α_B	-0.316	-0.400	-1.151	-0.244	-0.216	-0.324	-0.214	-0.083	-0.384
		(0.029)	(0.102)	(0.113)	(0.038)	(0.019)	(0.024)	(0.010)	(0.014)	(0.029)
DoW Prefs	Mon.	–	0.732	-0.333	0.217	-0.465	-0.499	–	0.059	0.135
		–	(0.102)	(0.081)	(0.075)	(0.082)	(0.089)	–	(0.046)	(0.085)
	Tues.	-0.178	0.711	-0.045	0.026	-0.293	-0.385	-0.205	-0.067	0.513
		(0.044)	(0.101)	(0.098)	(0.075)	(0.084)	(0.081)	(0.072)	(0.045)	(0.105)
	Wed.	-0.093	0.244	0.032	–	-0.340	-0.108	-0.108	-0.132	0.235
		(0.046)	(0.063)	(0.094)	–	(0.076)	(0.081)	(0.074)	(0.043)	(0.104)
	Thurs.	-0.068	0.092	-0.036	-0.076	–	-0.027	0.016	-0.182	0.222
		(0.042)	(0.052)	(0.075)	(0.071)	–	(0.082)	(0.052)	(0.041)	(0.082)
	Fri.	0.067	–	–	-0.177	-0.105	–	0.019	-0.229	0.222
		(0.042)	–	–	(0.069)	(0.076)	–	(0.051)	(0.044)	(0.058)
	Sat.	-0.185	-0.212	-0.268	-0.253	-0.412	-0.214	0.211	-0.389	-0.156
		(0.046)	(0.060)	(0.081)	(0.096)	(0.072)	(0.077)	(0.049)	(0.046)	(0.089)
	Sun.	0.046	0.416	0.011	0.025	-0.191	-0.231	0.146	–	–
		(0.047)	(0.073)	(0.076)	(0.074)	(0.070)	(0.085)	(0.052)	–	–
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.354	0.304	0.223	0.591	0.989	0.999	0.860	0.396	0.580
Summary										
Percent. of 0s		89.8	91.5	92.9	92.1	91.2	92.1	85.5	87.3	94.4
First stage R^2		0.773	0.764	0.703	0.870	0.854	0.812	0.669	0.750	0.788
Arrivals	A	3.060	1.449	0.809	1.408	4.233	2.593	11.489	5.900	0.863
Emp. Q	Q	0.527	0.310	0.098	0.315	0.161	0.146	0.353	0.667	0.222
		(0.00,3.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,3.00)	(0.00,2.00)
Model Q	$E[Q]$	0.535	0.310	0.097	0.315	0.171	0.152	0.381	0.687	0.223
		(0.07,1.54)	(0.02,1.05)	(0.01,0.35)	(0.02,1.15)	(0.04,0.48)	(0.03,0.41)	(0.10,1.35)	(0.14,1.85)	(0.03,0.69)
Elas	e	-1.070	-1.692	-1.880	-0.488	-0.580	-0.950	-1.179	-0.578	-0.889
		(-1.77,-0.53)	(-2.90,-0.77)	(-2.54,-0.94)	(-0.70,-0.21)	(-1.39,-0.39)	(-2.15,-0.49)	(-1.90,-0.78)	(-0.89,-0.19)	(-1.18,-0.62)
Number of Flights		1,027	927	393	698	179	191	217	842	776
Number of Dep. Dates		286	330	392	228	171	177	217	245	221
Number of Obs.		118,307	105,706	46,999	80,735	20,705	22,749	25,914	94,552	86,314

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 81: Demand Results Summary Table: Additional 50% Scaling Arrivals

Route		105	106	107	108	109	110	111	112	113
Parameter										
Leis. Price Sens.	α_L	-2.297	-1.054	-1.656	-0.769	-3.035	-2.228	-2.175	-0.795	-0.867
		(0.042)	(0.192)	(0.173)	(0.052)	(0.090)	(0.092)	(0.152)	(0.054)	(0.162)
Bus. Price Sens.	α_B	-0.128	-0.129	-0.214	-0.138	-0.141	-0.307	-0.061	-0.098	-0.101
		(0.020)	(0.027)	(0.022)	(0.031)	(0.031)	(0.077)	(0.015)	(0.016)	(0.022)
DoW Prefs	Mon.	0.050	-0.103	–	0.254	-0.136	-0.233	0.017	-0.021	0.103
		(0.074)	(0.085)	–	(0.065)	(0.045)	(0.094)	(0.054)	(0.041)	(0.046)
	Tues.	-0.178	-0.100	-0.008	0.209	–	0.001	0.013	–	–
		(0.071)	(0.079)	(0.059)	(0.071)	–	(0.093)	(0.066)	–	–
	Wed.	–	–	0.008	0.175	0.036	-0.209	0.086	0.167	-0.003
		–	–	(0.061)	(0.072)	(0.048)	(0.106)	(0.057)	(0.052)	(0.051)
	Thurs.	0.228	0.079	-0.030	0.180	-0.070	–	0.176	0.161	0.069
		(0.067)	(0.076)	(0.058)	(0.070)	(0.050)	–	(0.068)	(0.043)	(0.053)
	Fri.	0.214	0.065	-0.009	0.199	-0.160	-0.026	0.233	0.201	0.096
		(0.062)	(0.082)	(0.052)	(0.067)	(0.044)	(0.100)	(0.060)	(0.045)	(0.046)
	Sat.	-0.320	-0.244	-0.128	–	-0.401	-0.587	–	-0.216	-0.046
		(0.090)	(0.088)	(0.059)	–	(0.043)	(0.118)	–	(0.042)	(0.053)
	Sun.	-0.003	-0.138	0.070	0.653	-0.184	-0.397	-0.212	0.077	0.034
		(0.083)	(0.080)	(0.062)	(0.074)	(0.052)	(0.125)	(0.055)	(0.043)	(0.050)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.402	0.307	0.487	0.126	0.518	0.229	0.472	0.403	0.455
Summary										
Percent. of 0s		94.5	92.0	91.6	88.7	92.1	95.7	89.2	87.2	90.4
First stage R^2		0.742	0.749	0.752	0.817	0.752	0.828	0.781	0.756	0.773
Arrivals	A	0.952	0.995	2.207	1.618	4.045	0.398	2.763	5.591	2.652
Emp. Q	Q	0.180	0.110	0.256	0.179	0.488	0.102	0.291	0.670	0.264
		(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,3.00)	(0.00,1.00)	(0.00,2.00)	(0.00,3.00)	(0.00,2.00)
Model Q	$E[Q]$	0.181	0.111	0.260	0.178	0.499	0.102	0.293	0.691	0.267
		(0.02,0.64)	(0.01,0.37)	(0.04,0.76)	(0.03,0.63)	(0.05,1.67)	(0.00,0.47)	(0.03,0.95)	(0.15,1.80)	(0.05,0.75)
Elas	e	-0.496	-0.806	-0.698	-0.879	-0.307	-1.433	-0.335	-0.617	-0.596
		(-0.80,-0.25)	(-1.25,-0.24)	(-0.94,-0.39)	(-1.62,-0.34)	(-0.36,-0.24)	(-2.35,-0.30)	(-0.59,-0.11)	(-1.01,-0.20)	(-0.88,-0.22)
Number of Flights		976	396	753	381	1,528	711	582	823	767
Number of Dep. Dates		366	396	325	379	332	361	307	235	383
Number of Obs.		115,101	47,231	88,155	45,352	180,174	84,446	66,956	91,695	91,042

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 82: Demand Results Summary Table: Additional 50% Scaling Arrivals

Route		114	115	116	117	118	119	120	121	122
Parameter										
Leis. Price Sens.	α_L	-2.002	-1.772	-2.468	-2.241	-0.509	-0.450	-2.004	-0.432	-1.663
		(0.063)	(0.088)	(0.109)	(0.036)	(0.072)	(0.035)	(0.080)	(0.022)	(0.202)
Bus. Price Sens.	α_B	-0.589	-0.430	-0.526	-0.339	-0.273	-0.141	-0.257	-0.154	-0.917
		(0.034)	(0.046)	(0.035)	(0.054)	(0.046)	(0.016)	(0.050)	(0.023)	(0.113)
DoW Prefs	Mon.	–	0.203	0.209	0.112	-0.009	0.117	–	-0.081	-0.064
		–	(0.060)	(0.099)	(0.066)	(0.064)	(0.056)	–	(0.061)	(0.044)
	Tues.	0.019	0.198	0.172	0.114	-0.014	–	0.081	0.002	-0.080
		(0.074)	(0.050)	(0.127)	(0.065)	(0.066)	–	(0.052)	(0.067)	(0.049)
	Wed.	0.073	0.103	0.304	0.044	0.001	0.010	0.019	–	–
		(0.066)	(0.067)	(0.138)	(0.041)	(0.059)	(0.052)	(0.055)	–	–
	Thurs.	0.038	–	0.244	0.025	0.274	0.137	-0.023	0.230	0.088
		(0.075)	(0.059)	(0.100)	(0.060)	(0.054)	(0.053)	(0.047)	(0.055)	(0.044)
	Fri.	-0.081	-0.191	0.050	–	-0.039	0.081	-0.092	0.006	0.708
		(0.055)	(0.044)	(0.119)	–	(0.053)	(0.053)	(0.046)	(0.054)	(0.096)
	Sat.	-0.232	-0.168	–	-0.302	–	-0.114	-0.204	-0.161	0.666
		(0.073)	(0.065)	–	(0.050)	–	(0.053)	(0.039)	(0.057)	(0.099)
	Sun.	-0.138	–	-0.071	0.151	-0.056	0.014	-0.007	-0.013	0.608
		(0.052)	–	(0.099)	(0.053)	(0.056)	(0.056)	(0.046)	(0.058)	(0.082)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.274	0.386	0.442	0.536	0.247	0.297	0.459	0.373	0.195
Summary										
Percent. of 0s		95.2	95.2	94.9	94.2	90.6	88.2	92.2	90.3	95.0
First stage R^2		0.648	0.712	0.707	0.758	0.729	0.627	0.745	0.795	0.562
Arrivals	A	1.007	1.018	0.785	1.601	4.771	3.908	3.539	5.258	6.832
Emp. Q	Q	0.192	0.224	0.200	0.239	0.215	0.230	0.423	0.200	0.174
		(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.195	0.226	0.201	0.242	0.227	0.238	0.431	0.212	0.200
		(0.02,0.74)	(0.02,0.89)	(0.02,0.67)	(0.03,0.81)	(0.04,0.69)	(0.04,0.75)	(0.04,1.45)	(0.04,0.63)	(0.04,0.60)
Elas	e	-1.666	-1.151	-1.223	-0.753	-1.258	-0.798	-0.721	-0.859	-4.653
		(-2.17,-0.92)	(-1.42,-0.70)	(-1.52,-0.85)	(-0.94,-0.56)	(-1.68,-1.00)	(-1.24,-0.41)	(-0.83,-0.50)	(-1.25,-0.64)	(-6.16,-3.61)
Number of Flights		1,242	1,443	687	1,314	316	452	1,298	276	671
Number of Dep. Dates		371	363	198	384	210	378	314	215	362
Number of Obs.		147,288	170,376	77,032	155,366	37,711	53,729	150,869	32,599	80,043

Note: For the “parameter” rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the “summary” rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled “Percent. of 0s”, the r-squared of a regression of prices on the controls and instruments is in “First stage R^2”, the mean of the estimated posterior distribution for the arrivals process is in “A”, the average total number of purchases observed in the data is in “Emp. Q” with the 5th and 95th percentile of purchases in parentheses, our model’s prediction of the average total number of purchases is in “Model Q” with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled “Elas”. Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 83: Demand Results Summary Table: Additional 50% Scaling Arrivals

Route		123	124	125	126	127	128	129	130	131
Parameter										
Leis. Price Sens.	α_L	-2.465	-2.215	-1.118	-2.246	-2.330	-1.093	-1.254	-2.390	-1.081
		(0.116)	(0.335)	(0.117)	(0.112)	(0.061)	(0.464)	(0.064)	(0.064)	(0.067)
Bus. Price Sens.	α_B	-0.587	-0.250	-0.127	-0.414	-0.442	-0.189	-0.159	-0.243	-0.313
		(0.050)	(0.051)	(0.027)	(0.054)	(0.041)	(0.040)	(0.039)	(0.080)	(0.037)
DoW Prefs	Mon.	0.009	0.334	0.136	0.239	0.111	-0.209	–	0.520	0.130
		(0.048)	(0.085)	(0.082)	(0.041)	(0.058)	(0.082)	–	(0.059)	(0.070)
	Tues.	0.068	-0.005	–	0.339	0.188	-0.355	-0.387	0.488	0.150
		(0.056)	(0.084)	–	(0.045)	(0.083)	(0.087)	(0.064)	(0.090)	(0.077)
	Wed.	0.091	0.196	-0.021	0.220	0.334	-0.172	-0.456	0.099	0.131
		(0.054)	(0.082)	(0.083)	(0.036)	(0.071)	(0.075)	(0.064)	(0.065)	(0.077)
	Thurs.	–	0.293	-0.226	0.236	0.401	–	-0.279	0.303	-0.017
		–	(0.095)	(0.074)	(0.036)	(0.053)	–	(0.063)	(0.062)	(0.061)
	Fri.	-0.105	–	-0.210	0.187	-0.017	-0.294	-0.574	0.263	-0.034
		(0.051)	–	(0.077)	(0.035)	(0.060)	(0.073)	(0.063)	(0.068)	(0.063)
	Sat.	-0.112	0.087	-0.322	–	–	-0.470	-0.718	–	0.037
		(0.045)	(0.086)	(0.084)	–	–	(0.079)	(0.067)	–	(0.074)
	Sun.	0.082	0.140	0.268	0.128	-0.012	-0.297	0.230	0.168	–
		(0.070)	(0.083)	(0.079)	(0.039)	(0.061)	(0.080)	(0.059)	(0.070)	–
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.363	0.423	0.296	0.389	0.466	0.733	0.253	0.505	0.219
Summary										
Percent. of 0s		94.3	92.9	91.5	92.2	95.2	91.7	82.4	93.7	93.3
First stage R^2		0.677	0.834	0.785	0.742	0.741	0.779	0.800	0.713	0.652
Arrivals	A	2.047	1.233	0.996	4.199	1.022	3.115	2.317	1.529	1.168
Emp. Q	Q	0.309	0.085	0.116	0.493	0.228	0.128	0.307	0.291	0.170
		(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,3.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,1.00)
Model Q	$E[Q]$	0.315	0.086	0.116	0.504	0.230	0.132	0.305	0.293	0.171
		(0.04,1.14)	(0.02,0.23)	(0.01,0.40)	(0.06,1.70)	(0.02,0.89)	(0.02,0.41)	(0.04,1.14)	(0.03,0.89)	(0.01,0.59)
Elas	e	-1.273	-0.681	-0.866	-1.043	-0.955	-0.622	-1.419	-0.622	-1.333
		(-1.42,-1.04)	(-0.84,-0.52)	(-1.32,-0.25)	(-1.15,-0.80)	(-1.15,-0.69)	(-0.83,-0.45)	(-2.70,-0.27)	(-0.76,-0.44)	(-1.87,-0.70)
Number of Flights		1,403	371	397	1,495	1,372	196	391	790	622
Number of Dep. Dates		319	371	396	315	345	192	391	226	308
Number of Obs.		164,088	44,200	47,306	171,177	162,637	22,953	46,734	92,967	69,175

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.

Table 84: Demand Results Summary Table: Additional 50% Scaling Arrivals

Route		132	133	134	135	136	137	138	139	140
Parameter										
Leis. Price Sens.	α_L	-2.950	-2.422	-0.884	-2.636	-1.532	-2.796	-1.559	-3.142	-1.235
		(0.114)	(0.079)	(0.065)	(0.204)	(0.067)	(0.077)	(0.044)	(0.265)	(0.064)
Bus. Price Sens.	α_B	-0.491	-1.415	-0.171	-0.192	-0.098	-0.265	-0.078	-0.432	-0.169
		(0.053)	(0.081)	(0.031)	(0.026)	(0.018)	(0.018)	(0.015)	(0.064)	(0.033)
DoW Prefs	Mon.	0.082	0.434	0.175	-0.045	0.166	-0.121	-0.258	-0.207	0.179
		(0.071)	(0.085)	(0.069)	(0.068)	(0.062)	(0.069)	(0.073)	(0.070)	(0.067)
	Tues.	0.002	0.181	0.113	-0.180	-0.078	-0.078	-0.252	0.103	–
		(0.063)	(0.091)	(0.077)	(0.079)	(0.066)	(0.080)	(0.072)	(0.087)	–
	Wed.	0.230	–	0.179	-0.204	–	–	0.360	–	-0.206
		(0.064)	–	(0.068)	(0.079)	–	–	(0.074)	–	(0.069)
	Thurs.	0.129	0.051	0.164	-0.114	0.030	-0.019	1.554	0.594	0.110
		(0.066)	(0.087)	(0.065)	(0.088)	(0.062)	(0.090)	(0.090)	(0.100)	(0.068)
	Fri.	0.192	0.040	0.261	-0.166	-0.028	0.147	-0.225	-0.135	0.285
		(0.067)	(0.087)	(0.065)	(0.077)	(0.062)	(0.067)	(0.069)	(0.078)	(0.065)
	Sat.	–	-0.008	–	-0.279	-0.320	-0.201	-0.431	-0.256	-0.064
		–	(0.087)	–	(0.085)	(0.067)	(0.073)	(0.099)	(0.070)	(0.068)
	Sun.	0.064	0.147	0.232	–	-0.031	-0.074	–	-0.517	-0.248
		(0.067)	(0.084)	(0.066)	–	(0.065)	(0.057)	–	(0.073)	(0.066)
Week FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
ToD FE		Y	Y	Y	Y	Y	Y	Y	Y	Y
Pr(Bus)	γ	0.522	0.181	0.296	0.811	0.468	0.328	0.257	0.388	0.295
Summary										
Percent. of 0s		92.6	91.0	89.6	91.7	90.6	95.2	83.8	92.6	83.4
First stage R^2		0.834	0.817	0.754	0.799	0.793	0.762	0.735	0.759	0.778
Arrivals	A	1.592	1.121	1.326	3.437	1.644	2.169	1.460	1.854	1.653
Emp. Q	Q	0.221	0.146	0.155	0.127	0.244	0.170	0.283	0.397	0.283
		(0.00,2.00)	(0.00,1.00)	(0.00,1.00)	(0.00,1.00)	(0.00,2.00)	(0.00,1.00)	(0.00,2.00)	(0.00,2.00)	(0.00,2.00)
Model Q	$E[Q]$	0.223	0.145	0.154	0.133	0.244	0.174	0.277	0.399	0.276
		(0.02,0.80)	(0.01,0.59)	(0.02,0.53)	(0.02,0.40)	(0.04,0.70)	(0.02,0.61)	(0.02,1.14)	(0.02,1.64)	(0.04,0.99)
Elas	e	-0.846	-2.063	-0.922	-0.565	-0.582	-0.668	-1.409	-0.954	-1.269
		(-1.30,-0.55)	(-2.63,-1.37)	(-1.65,-0.26)	(-0.92,-0.42)	(-1.01,-0.20)	(-0.84,-0.51)	(-3.21,-0.16)	(-1.22,-0.62)	(-2.39,-0.21)
Number of Flights		623	318	389	191	671	718	336	794	387
Number of Dep. Dates		278	299	389	188	338	267	335	193	387
Number of Obs.		73,598	37,682	46,464	22,483	76,893	82,972	39,900	90,762	46,205

Note: For the "parameter" rows we report the mean and standard deviation (in parentheses) of the estimated posterior distributions of the preference parameters excluding the week and time of departure (ToD) fixed effects. For the "summary" rows, we provide additional information about the estimates and underlying data. The fraction of observations in the data that have no purchases is reported in the row labeled "Percent. of 0s", the r-squared of a regression of prices on the controls and instruments is in "First stage R^2", the mean of the estimated posterior distribution for the arrivals process is in "A", the average total number of purchases observed in the data is in "Emp. Q" with the 5th and 95th percentile of purchases in parentheses, our model's prediction of the average total number of purchases is in "Model Q" with the 5th and 95th percentile of predicted purchases in parentheses, and the estimated mean own-price elasticities are reported in the row labeled "Elas". Finally, we report the number of flights, departure days, and total number of observations used in estimation. All parameters and summary values are route specific.