*Econometrica Supplementary Material*

# SUPPLEMENT TO "THE WELFARE EFFECTS OF DYNAMIC PRICING: EVIDENCE FROM AIRLINE MARKETS"

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## APPENDIX A: ADDITIONAL FIGURES AND SUPPORTING ANALYSIS

### A.1. *Pricing Heterogeneity Across Routes*

SEE FIGURES 7 and 8.

### A.2. *Fare Dynamics in Competitive Markets*

See Figure 9.

### A.3. *Price Discrimination Across Aircraft Cabins and Over Time*

See Figure 10.

### A.4. *Connecting Fare Response to Nonstop Bookings*

See Figure 11.

### A.5. *Parameter Estimates and Counterfactual Results Across Routes*

See Figures 12 and 13.

## APPENDIX B: ROUTE SELECTION CRITERIA AND ANALYSIS

Using the publicly available DB1B data, I select origin-destination pairs to study. These data contain a 10 percent sample of bookings and are at the quarterly level. The data contain neither the date of travel nor the date of purchase.

I first combine traffic from all airports in which there exists a nearby airport within sixty miles. This combines, for example, Laguardia (LGA), John F. Kennedy (JFK), and Newark (EWR).[27] Next, I focus on ODs with a nonstop option; this reduces the number of potential markets studied from 73,000 to 9800. Over 40 percent of these markets have a single carrier providing nonstop service and this subset makes up a total of 14 percent of

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[27]This creates the following groupings: (DAB, MCO, SFB); (OGD, SLC); (EWN, OAJ); (KOA, MUE); (SBP, SMX); (AZA, PHX); (BRO, HRL, MFE); (CMI, DEC); (PIE, SRQ, TPA); (MHT, PSM); (BUR, LAX, LGB, ONT, SNA); (BTV, PBG); (BFM, MOB); (HHH, SAV); (DAL, DFW); (EVV, OWB); (MSS, OGS); (BQN, MAZ); (PSG, WRG); (HOU, IAH); (ORF, PHF); (FAT, VIS); (ATW, GRB); (PAE, SEA); (LNS, MDT); (CLT, USA); (OAK, SFO, SJC); (AOO, JST, LBE); (BLV, STL); (CPX, SPB, STT, VQS); (LWS, PUW); (BGM, ELM, ITH); (BGR, BHB); (ACK, EWB, HYA, MVY, PVC, PVD, BOS); (BWI, DCA, IAD); (CLD, SAN); (CHO, SHD); (ASE, EGE); (SCM, VAK); (GYY, MDW, ORD); (BUF, IAG); (CMH, LCK); (PHL, TTN); (PGD, RSW); (FLL, MIA); (HNM, JHM, LNY, LUP, MKK, OGG); (MCE, MOD, SCK); (LEB, RUT); (CKB, MGW); (GLV, WMO); (EWR, HPN, HVN, ISP, JFK, LGA, SWF).

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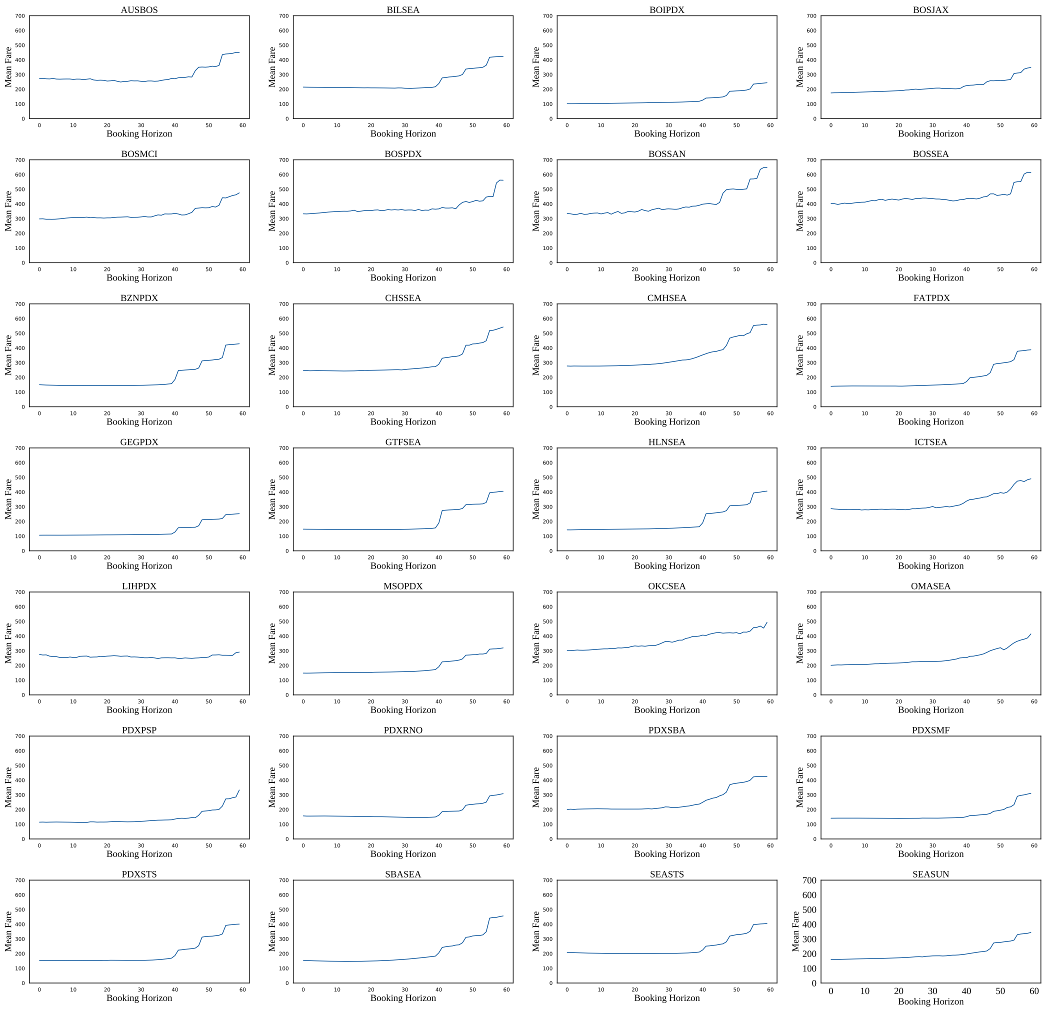


FIGURE 7.—Average fares over time by Route. Note: Average fares over time for each route separately. This analysis combines origin-destination and destination-origin fares. Both axes are common across all plots.

OD traffic in the United States. I then implement the following cleaning criteria: (1) total quarterly traffic, including connecting traffic with up to four stops, exceeds 600 passengers;[28] (2) a single carrier operates nonstop on the OD leg. This reduces the number of potential markets by over half, to roughly 3900.

Next, I calculate the following statistics: (1) OD nonstop traffic; (2) OD total traffic (including one-stop connections, all the way up to four-stop connections); (3) passenger traffic connecting to OD or connecting from OD, which again is allowed to have at most

[28]This is calculated as half a fifty-seat plane, offering at least weekend service (eight monthly flights), for the quarter, for example, .5*50*8*3 = 600. This level of the criterion is not critical, but a minimum passenger threshold of 10 (scaling 1 passenger up to 10, as it is a 10% sample) is important because it removes erroneous entries in the DB1B. For example, in 2012, United Airlines did not operate nonstop between Lehigh Valley International Airport (ABE) and Nashville (BNA). Another method is to look at scheduled service in the T100 segment tables.

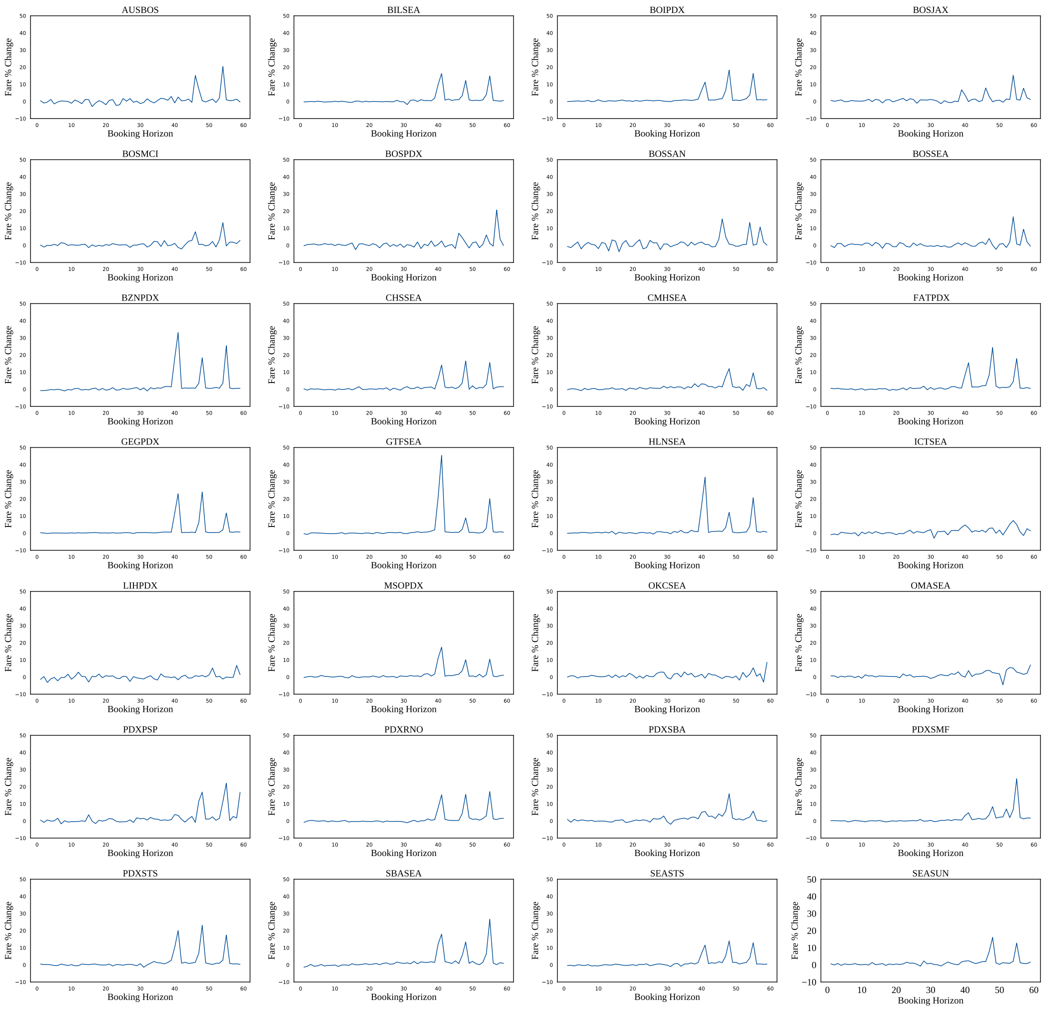


FIGURE 8.—Percentage change in fares over time by route. Note: Percent change in average fares over time for each route separately. This analysis combines origin-destination and destination-origin fares. Both axes are common across all plots.

five legs. The fraction (1)/(2) calculates the percentage of traffic flying nonstop. The fraction $(1)/[(1) + (3)]$ calculates the percentage of traffic not connecting. Shown another way,

$$\text{FracNonstop} := \frac{\text{Passengers OD Nonstop}}{(\text{Passengers OD Nonstop}) + (\text{Passengers OD} \geq 1 \text{ Stops})}$$

$$:= \frac{(O \to D)}{(O \to D) + (O \to C \to D)},$$

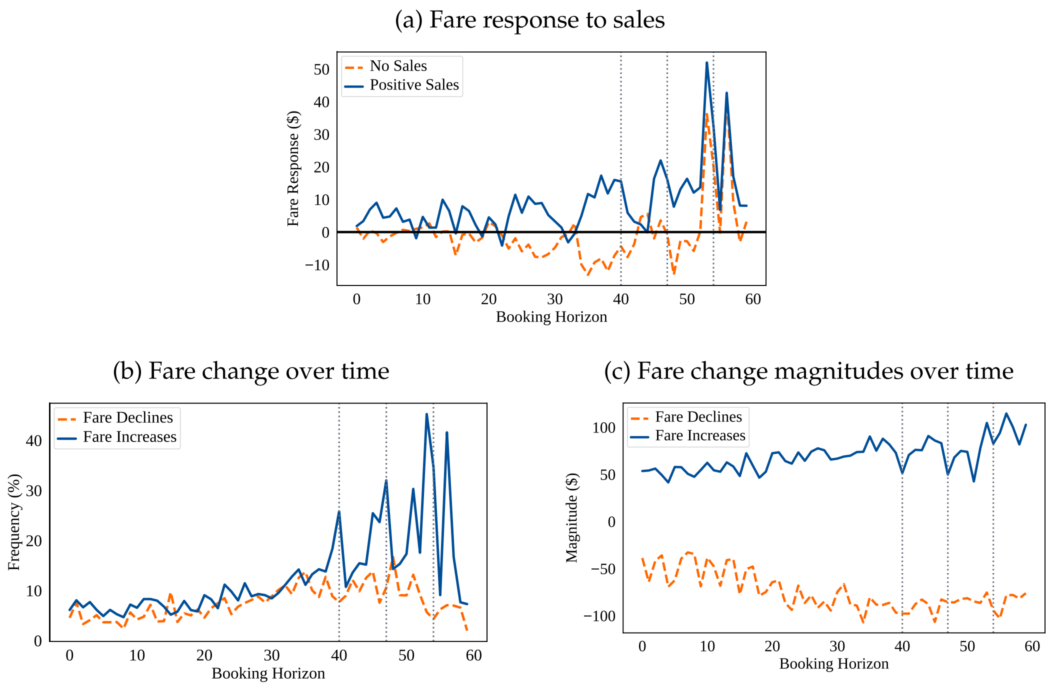


FIGURE 9.—Fare dynamics in competitive markets. Note: Recreation of Figure 1(b) through Figure 1(d) for markets with nonstop competition. (a) Fare response to own bookings (no bookings) over time. (b) Frequency of fare increases and decreases over time. (c) Magnitude of fare increases and decreases over time.

where $C$ denotes potential connections for passengers flying on OD. Using similar notation,

$$\text{FracNotConnecting} := \frac{(O \to D)}{(O \to D) + (C \to O \to D) + (O \to D \to C)},$$

which is simply the fraction of passengers on planes flying OD that are not connecting on either end.

Single carrier markets have percent nonstop and percent non-connecting means of 76 percent and 57 percent as compared with 83 percent and 61 percent for competitive markets (medians of 82 percent, 56 percent, 88 percent, 62 percent, respectively). I limit myself to markets with at most 15,000 monthly passengers. This is to keep the data collection process manageable.

The two fractions are negatively correlated ($\rho = -0.33$); each is correlated with distance. The correlation between percentage non-connecting and distance is 0.24; ODs that are closer together have higher connecting traffic. The correlation between percentage nonstop and distance is $-0.52$; ODs that are closer together have a higher percentage of nonstop traffic.

Markets with high nonstop percentages and low connecting percentages are ideal because changes in seat maps are likely to be attributed to the correct itinerary, and hence, fare. One important caveat to this approach is that markets with a high nonstop percentage are also closer together, which implies there may be alternative modes of transportation, for example, a train, that is relevant for airline demand. For example, in 2019, there

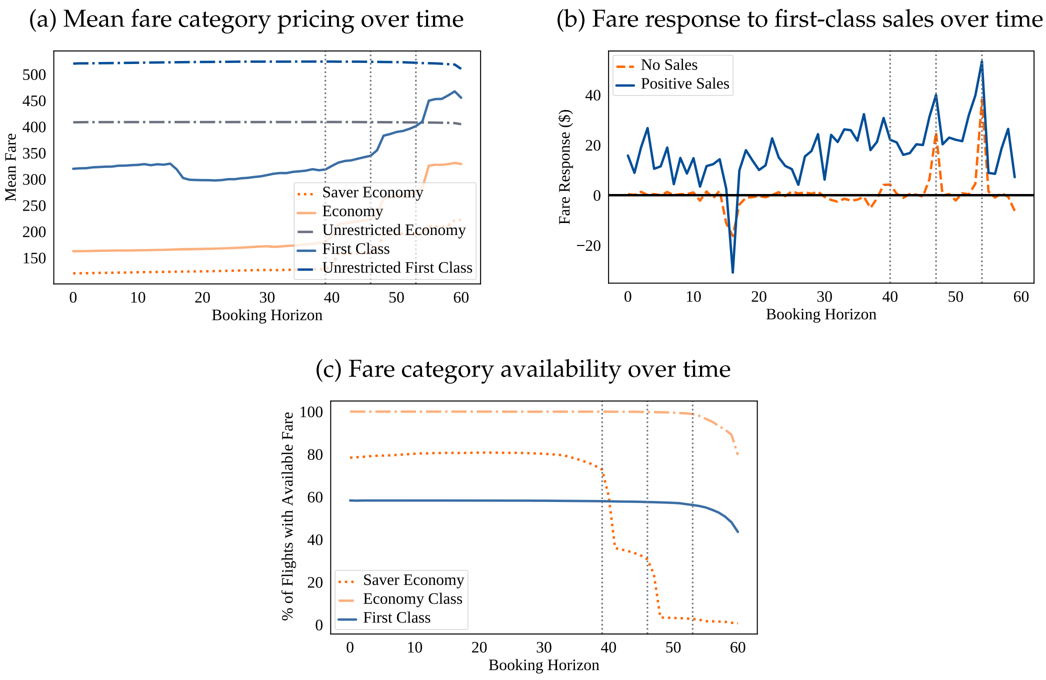


FIGURE 10.—Fare category pricing dynamics. Note: (a) Mean fares of different fare categories over time. Full-fare (refundable) tickets for both economy and first class are flat over time. Average fares for saver-economy, economy, and first-class tickets rise over time. The gap in fares between saver-economy and economy prices grows as the departure date approaches. (b) Recreation of Figure 1(b) for first class. Compared to economy class, the presence of APDs is diminished in first class, and fare increases are more pronounced throughout the booking horizon. (c) Percentage of flights that offer observed fare categories over time. First-class denominator is the number of flights with first class, not the number of flights in the sample. Close to departure, economy fare availability abruptly drops, suggesting that the spike in load factor shown in Figure 1(a) captures last-minute bookings. Economy fares rise and saver-economy availability declines.

exist 556 ODs with nonstop and non-connecting fractions above the 95 percent threshold. Of those ODs, 523 are operated by low-cost carriers Allegiant Air and Spirit Airlines. Unfortunately, both airlines charge for a seat assignment; thus, utilizing seat maps to determine bookings will likely be inaccurate. The next two carriers that meet threshold criteria (for nonstop and non-connecting traffic) are Alaska Airlines and JetBlue Airways.

I select fifty ODs and concentrate data collection on two carriers, JetBlue Airways and Alaska Airlines, such that both seat map and airfare data could be collected. The other carriers included in the data are Delta Air Lines and Frontier Airlines. In addition, for a comparison in the descriptive analysis, I collect data on six duopoly markets.[29] In Figure 14, I map the markets, and in Table VII, I provide a dictionary for the airport codes. The data were collected in two phases: The data on markets operated by Delta and JetBlue were collected in 2012, and the data for Alaska Air Lines were collected in 2019. Prices for data collected in 2012 are adjusted for inflation.

In Figure 15, I depict all OD pairs in the DB1B data that meet the thresholds stated above. Each dot corresponds to an OD pair. The vertical axis reports the percentage

[29]The city pair Boston, MA - Kansas City, MO was a duopoly market, with nonstop offered by both Delta Air Lines and Frontier Airlines in 2012. Frontier then exited the market.

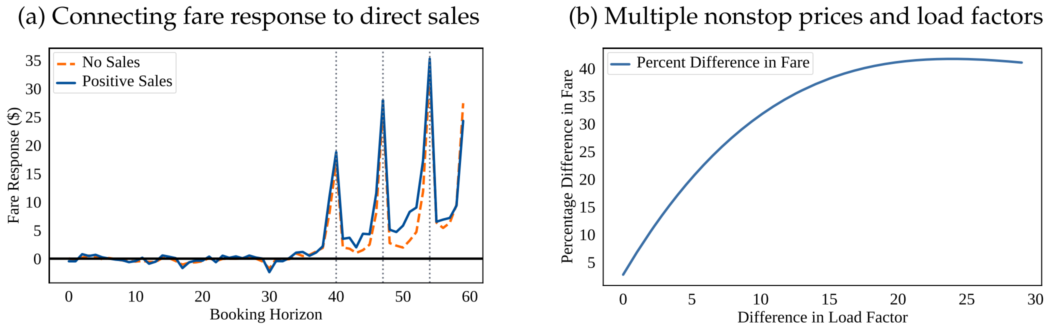


FIGURE 11.—Pricing effects on other itineraries. Note: (a) Recreation of Figure 1(b), but with connecting fares instead of direct fares. The connecting fare is the average fare among connecting flight options for the same carrier, departure date, and booking date. Evidence suggests that connecting fares are unaffected by nonstop bookings. (b) Fourth-order polynomial fit of a regression of the percent difference in fares on the percent difference in load factor when a carrier operates two nonstop flights a day. When flights have the same load factor, average difference in fares is 0.6 percent. The line is upward sloping, meaning that the flight with the higher load factor is, on average, more expensive.

(0–100) of non-connecting traffic. The horizontal axis reports the percentage of nonstop traffic. The left panel (a) includes all markets, and the right panel (b) removes Allegiant and Spirit because of the fee charged to select seats. These 556 ODs removed in (b) lie mostly along the top of the graph, corresponding to markets with 100 percent non-connecting traffic. The red squares show the markets selected for data collection and analysis. The dashed gray lines show the mean of each statistic and the solid black line depicts the fit of a linear simple regression.

The graphs show the negative correlation between the two statistics previously mentioned, with a large cluster of ODs having close to 100 percent nonstop traffic but also very high levels of connecting traffic. For this study, "ideal" markets arguably lie in the upper right of the graph. These are markets in which most consumers travel nonstop (versus one-stop) and do not connect to other flights. Note that this region is less dense compared with other areas in the graph. The graphs show that all but eight (panel a) or five (panel b) of the selected markets appear above the regression line, and most lie in the upper-right region of the graph.

In Table VIII, I provide traffic and price statistics in the DB1B for each OD in the sample. Note that OD fares are very similar to DO (the reverse) fares in the DB1B, and I use this finding in order to aggregate observations in estimation. Finally, one-stop fares are not necessarily cheaper than nonstop options. For example, nonstop fares from Billings, MT to Seattle, WA are cheaper than one-stop connections.

## APPENDIX C: INFERENCE AND ACCURACY OF SEAT MAPS

Seat maps may not accurately represent flight loads if consumers do not select seats at the time of booking. This measurement error would systematically understate sales early on, but then overstate last-minute sales when consumers without seat assignments are assigned seats. Ideally, the severity of measurement error can be measured by matching changes in seat maps with bookings; however, this is impossible with publicly available data.

I perform two analyses to gauge the magnitude of the measurement error in using seat maps.

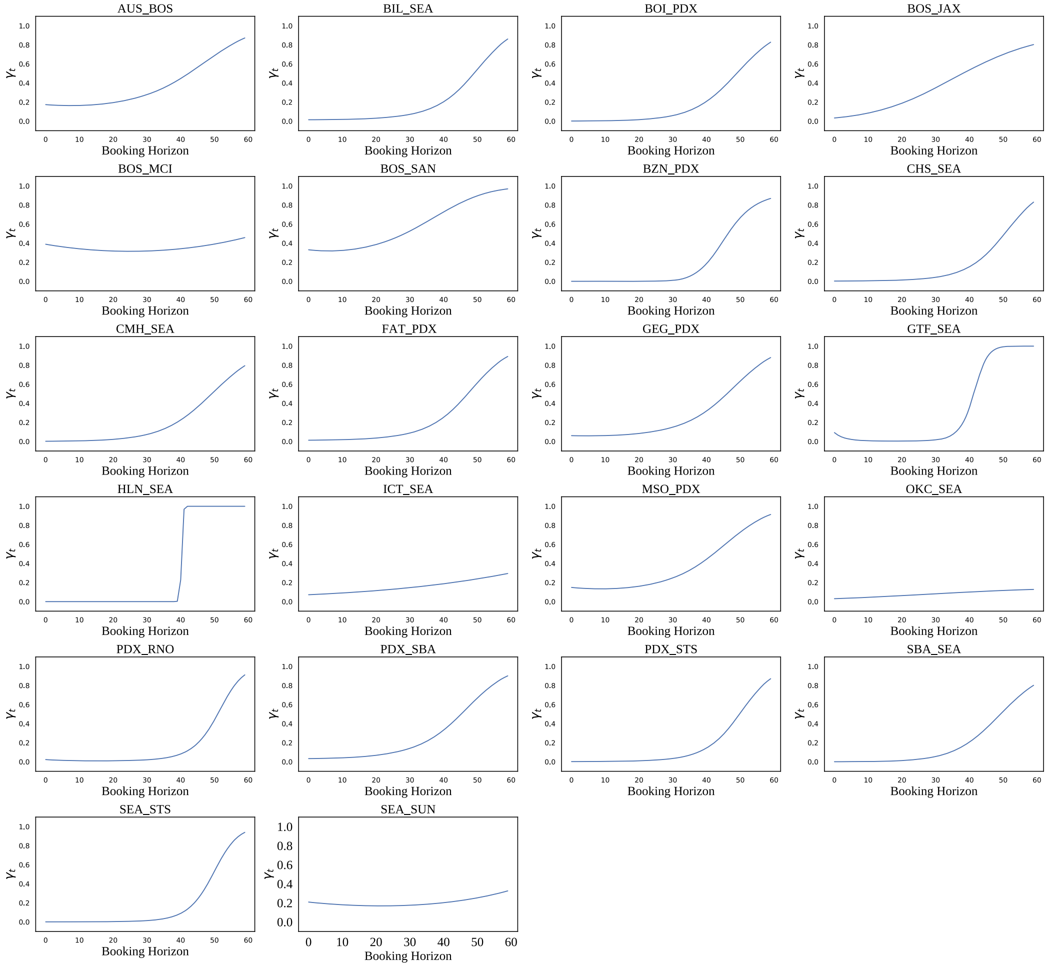


FIGURE 12.—Fitted values of $\gamma_t$ over time for each route. Note: Probability that an arriving consumer is of the business type over time, by route.

First, I match monthly enplanements using my seat maps aggregated on the day of departure with actual monthly enplanements reported in the T100 Segment tables. These tables record the total number of monthly enplanements by airline and route. I make two adjustments. First, because I do not observe first-class cabins in the 2012 sample, I assume first class goes out at 100% full and subtract off this passenger number using the size of the first-class cabin as recorded from the plane types in the T100. Second, because the number of observed flights can differ, for example, due to cancellations, flight number changes cause data collection to end, or flights are not tracked for 60 days, I reconcile any differences in the number of departures by adding or subtracting the average observed flight load times the count difference. In Figure 16, I provide a scatter plot that compares the two statistics. Most points closely follow the 45-degree line, and I find seat maps overstate recorded enplanements, with the median difference being three percent. Some of this difference could be driven by last-minute cancellations.

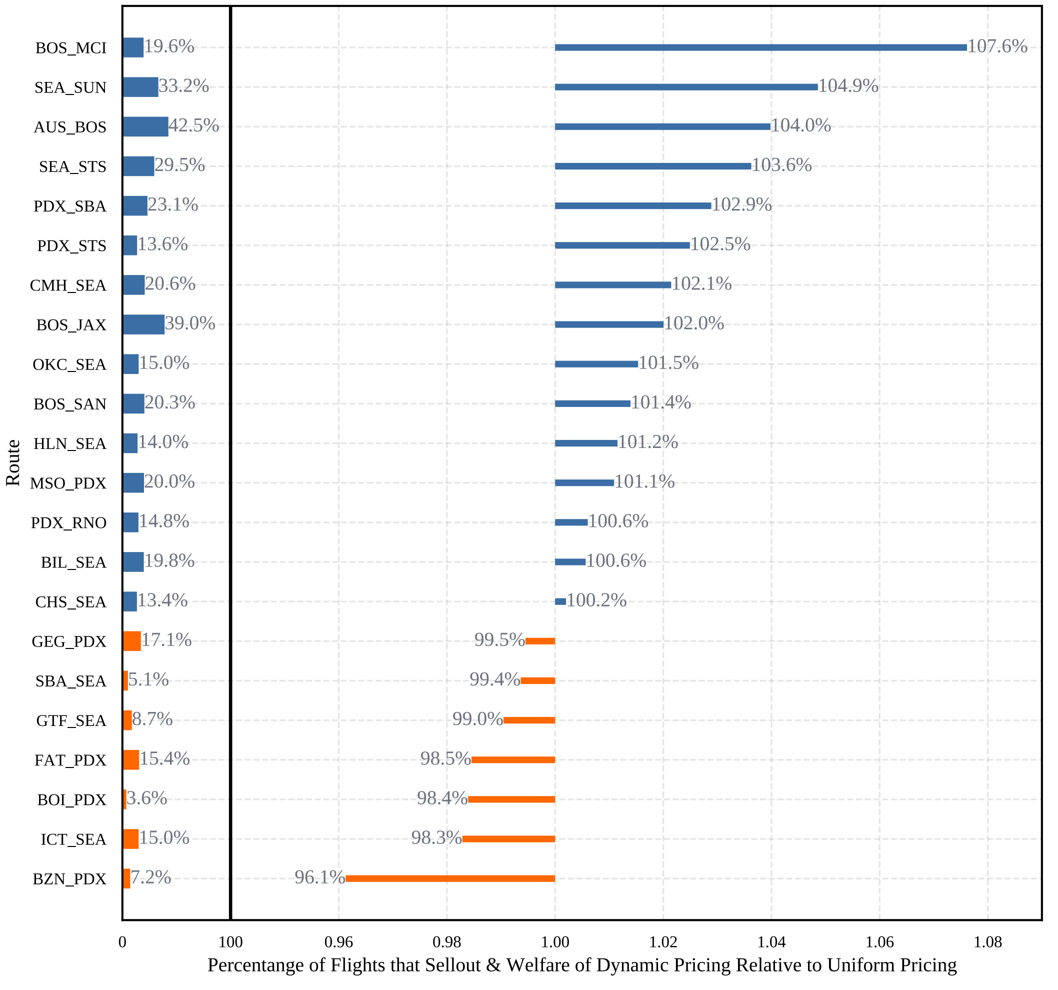


FIGURE 13.—Welfare effects of dynamic pricing for each route. Note: (Left) The percentage of flights that sell out on or before the departure date. (Right) Welfare under dynamic pricing over welfare under uniform pricing. Numbers above 100% (top, blue) indicate welfare is higher under dynamic pricing than uniform pricing.

Second, I create a new data set that allows me to estimate seat-map measurement error for each day before departure. The mobile version of United.com allowed users to examine seat maps for upcoming flights. In addition, for premium cabins, the airline reports the number of consumers booked into the cabin. I randomly select flights, departure dates, and search dates in 2012. In total, I obtain 15,567 observations. With these data, I find that seat maps understate reported load factor by 2.3 percent, or around one to two seats on average.

I plot the average measurement error by day before departure as well as a polynomial smooth of the data in Figure 17. I find the difference ranges from zero to five percent across days, or at most four seats. This suggests seat maps are useful for recovering bookings as the departure date approaches.

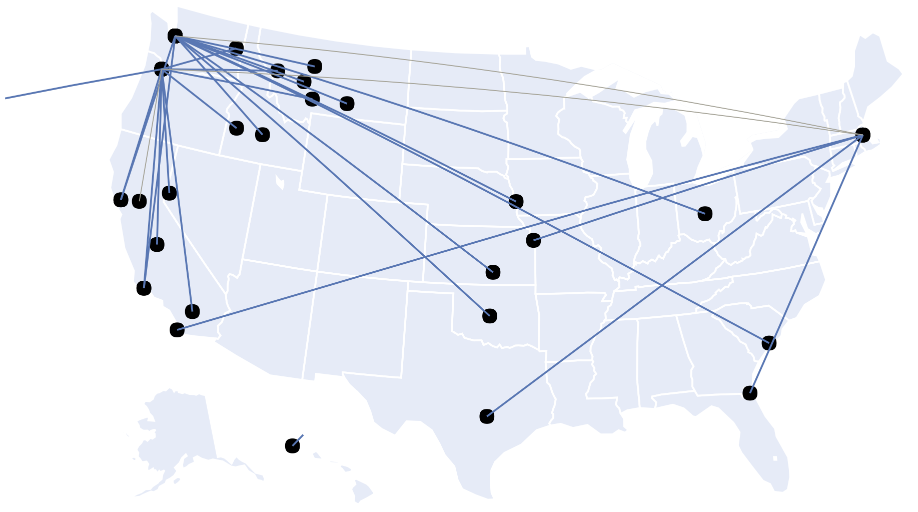

FIGURE 14.—Markets of study. Note: Map of the markets selected for study. All of the markets either start or end at Seattle, WI; Portland, OR; and Boston, MA.

## APPENDIX D: EVIDENCE OF DYNAMIC DEMAND IN AIRLINE MARKETS

There are noticeable jumps in prices over time; however, the booking curve for flights is smooth. If consumers are aware that fares tend to increase sharply around APD requirements, and they can strategically enter into the market, we should expect to see bunching in sales before APDs expire and few sales after expiration.

I investigate bunching (strategic purchasing timing) by modeling the booking curve as a function of time and include dummy variables for the day-before-departure (DFD) times immediately before AP fare expires. Table IX reports regression results under three fixed effects specifications. I find insignificant bunching at the fourteen-day AP expiration. I find negative bunching at the three-day and twenty-one-day AP expiration, meaning sales are lower prior to the price increases. Finally, I find a positive and significant coefficient for the seven-day AP requirement; that is, sales are higher before the usual seven-

TABLE VII

AIRPORT CODE LOOKUP.

| Airport Code | City | Airport Code | City |
|---|---|---|---|
| AUS | Austin, TX | JAX | Jacksonville, FL |
| BIL | Billings, MT | LIH | Lihue, HI |
| BOI | Boise, ID | MSO | Missoula, MT |
| BOS | Boston, MA | OKC | Oklahoma, OK |
| BZN | Bozeman, MT | OMA | Omaha, NE |
| CHS | Charleston, SC | PDX | Portland, OR |
| CMH | Columbus, OH | PSP | Palm Springs, CA |
| FAT | Fresno, CA | RNO | Reno, NV |
| GEG | Spokane, WA | SAN | San Diego, CA |
| GTF | Great Falls, MT | SBA | Santa Barbara, CA |
| HLN | Helena, MT | STS | Santa Rosa, CA |
| ICT | Wichita, KS | SUN | Sun Valley, ID |

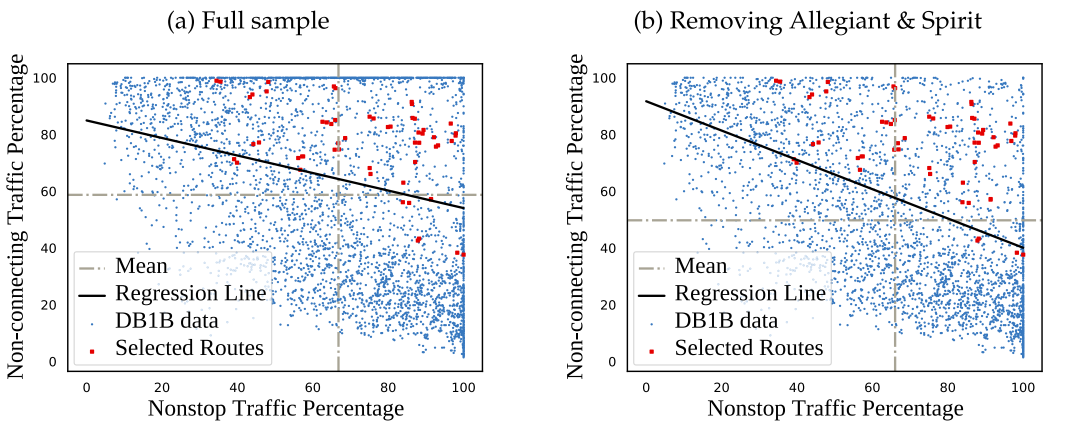


FIGURE 15.—Nonstop and non-connecting traffic in the DB1B. Note: (a) Percentage nonstop traffic and percentage non-connecting traffic for markets that meet selection criteria in the DB1B data. (b) Repeat of (a), excluding markets operated by Allegiant and Spirit.

day fare increase. It may be that at least some consumers anticipate price hikes and time their purchases accordingly. For example, Li, Granados, and Netessine (2014) estimated that between 5 and 20 percent of consumers dynamically substitute across days.

I also investigate the incentive to wait by changing the estimated model in the following way: after consumers arrive, each consumer has the option to buy a ticket, choose not to travel, or wait one additional day to decide. By choosing to wait, each consumer retains her private valuations (the $\varepsilon$'s) for traveling but may be offered a new price tomorrow. Consumers have rational expectations regarding future prices. However, in order to wait, each consumer has to pay a transaction cost $\phi_i$. This cost reflects the disutility consumers incur when needing to return to the market in the next period.

I derive a waiting cost $\overline{\phi}$ such that if all consumers have a waiting cost at least as high as $\overline{\phi}$, then no one will wait. I then calculate the transaction costs.

Dropping the $i$, $t$, $s$ subscripts, the choice set of a consumer arriving at time $t$ in a model of waiting is

$$\max\{\varepsilon_0, \beta - \alpha p + \varepsilon_1, \mathrm{EU}^{\text{wait}} - \phi\},$$

where $\mathrm{EU}^{\text{wait}}$ is the expected value of waiting one more period. This expected utility can be written as

$$\mathrm{EU}^{\text{wait}} = \mathbb{E}\big[\max\{\varepsilon_0, \beta - \alpha p_{t+1} + \varepsilon_1\}\big].$$

To derive $\overline{\phi}$, I first investigate the decision to wait for the marginal consumer, or the consumer such that $\varepsilon_0 = \beta - \alpha p + \varepsilon_1$. This consumer has no incentive to wait if the price tomorrow is at least as high as today. If the price drops, the gain from waiting is

$$\begin{aligned} u_{t+1} - u_t &= (\beta - \alpha p_{t+1} + \varepsilon_1) - (\beta - \alpha p + \varepsilon_1) \\ &= \alpha(p - p_{t+1}). \end{aligned}$$

For this marginal consumer, the expected gains from waiting are

$$\Pr(p_{t+1} < p)\mathbb{E}\big[\alpha(p - p_{t+1}) | p_{t+1} < p\big].$$

TABLE VIII

MARKETS SUMMARY.

| Origin | Dest. | $\text{Nonstop}_{\text{OD}}$ | $\text{Nonstop}_{\text{DO}}$ | $\text{Total}_{\text{OD}}$ | $\text{Total}_{\text{DO}}$ | $\text{Connect.}_{\text{OD}}$ | $\text{Connect.}_{\text{DO}}$ | $\text{Fare}_{\text{OD}}$ | $\text{Fare}_{\text{DO}}$ | One-stop Fare |
|---|---|---|---|---|---|---|---|---|---|---|
| AUS | BOS | 7572 | 7277 | 7677 | 7352 | 13,905 | 14,090 | 283 | 273 | 253 |
| BIL | SEA | 4830 | 4960 | 8487 | 8762 | 895 | 800 | 213 | 216 | 280 |
| BOI | PDX | 24,532 | 24,935 | 32,412 | 32,735 | 1937 | 1805 | 147 | 149 | 146 |
| BOS | JAX | 12,190 | 12,360 | 12,575 | 12,822 | 6310 | 6295 | 194 | 194 | 206 |
| BOS | MCI | 7352 | 7457 | 7747 | 7582 | 7895 | 7820 | 233 | 232 | 267 |
| BOS | PDX | 11,260 | 11,390 | 13,302 | 13,555 | 6622 | 6387 | 293 | 296 | 311 |
| BOS | SAN | 14,657 | 14,582 | 15,600 | 15,647 | 18,672 | 18,977 | 315 | 313 | 291 |
| BOS | SEA | 24,372 | 24,267 | 28,837 | 29,172 | 12,372 | 12,967 | 322 | 324 | 312 |
| BZN | PDX | 3402 | 3340 | 4955 | 4977 | 1075 | 1012 | 183 | 182 | 212 |
| CHS | SEA | 5812 | 5877 | 8067 | 8135 | 4477 | 4357 | 272 | 264 | 272 |
| CMH | SEA | 7486 | 7450 | 9706 | 9733 | 9016 | 9493 | 272 | 275 | 238 |
| FAT | PDX | 7170 | 7325 | 9252 | 9470 | 1000 | 950 | 168 | 168 | 196 |
| GEG | PDX | 19,055 | 19,307 | 33,387 | 33,712 | 1812 | 1825 | 157 | 157 | 144 |
| GTF | SEA | 2412 | 2467 | 6430 | 6537 | 0 | 37 | 202 | 200 | 309 |
| HLN | SEA | 1867 | 1852 | 4302 | 4330 | 250 | 255 | 188 | 184 | 290 |
| ICT | SEA | 3937 | 3950 | 5105 | 5277 | 2052 | 2107 | 220 | 228 | 232 |
| LIH | PDX | 5486 | 5510 | 8203 | 7633 | 4070 | 3953 | 279 | 277 | 327 |
| MSO | PDX | 3497 | 3347 | 4967 | 5320 | 505 | 632 | 173 | 168 | 233 |
| OKC | SEA | 4102 | 4120 | 5855 | 5765 | 6367 | 6587 | 253 | 253 | 207 |
| OMA | SEA | 8570 | 8957 | 11,412 | 11,385 | 4315 | 4110 | 202 | 196 | 214 |
| PDX | PSP | 17,476 | 18,103 | 19,046 | 19,890 | 2733 | 2853 | 167 | 172 | 207 |
| PDX | RNO | 11,600 | 11,682 | 14,355 | 14,282 | 1555 | 1360 | 159 | 160 | 165 |
| PDX | SBA | 4182 | 4337 | 4832 | 5052 | 1420 | 1405 | 209 | 210 | 184 |
| PDX | SMF | 43,420 | 43,217 | 53,975 | 54,280 | 912 | 932 | 159 | 159 | 205 |
| PDX | STS | 5000 | 5112 | 5935 | 6502 | 142 | 137 | 183 | 186 | 234 |
| SBA | SEA | 7602 | 7637 | 9190 | 9225 | 1940 | 1885 | 188 | 186 | 187 |
| SEA | STS | 5000 | 4912 | 6367 | 6155 | 400 | 520 | 200 | 199 | 226 |
| SEA | SUN | 2702 | 2470 | 3167 | 2887 | 312 | 300 | 184 | 184 | 256 |
| All Markets | | 9906 | | 12,738 | | 4050 | | 215 | | 236 |

*Note*: Origin-destination (OD) statistics for the markets included in the sample. Summary statistics calculated as the quarterly average in the year in which data were collected. 2019 data are summarized with the three available quarters. 2012 fare data are adjusted for inflation. The All Markets row summarizes all ODs in the DB1B data, including all observations with less than five connections. The subscript OD denotes the Origin and Destination columns; DO denotes the reverse routing. (PDX,SMF), (SEA,BOS), and (BOS,PDX) are oligopoly markets. (BOS,MCI) was a duopoly market prior to the exit of Frontier. All markets operated by Alaska, except (BOS,MCI) [Delta], (AUS,BOS) [JetBlue], (BOS,JAX) [JetBlue], and (BOS,SAN) [JetBlue].

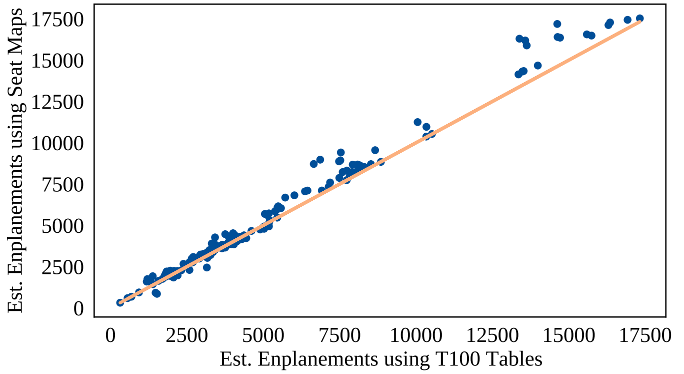


FIGURE 16.—Estimated seat map measurement error at the monthly level. Note: Measurement error estimated by comparing monthly enplanements, using the T100 Tables and aggregating seat maps to the monthly level. The solid line reflects zero measurement error.

Hence, an indifferent consumer will not wait if $\phi_i > \overline{\phi} = \Pr(p_{t+1} < p)\mathbb{E}[\alpha(p - p_{t+1})| p_{t+1} < p]$. This leads to the following proposition.

PROPOSITION: *With* $\overline{\phi} = \Pr(p_{t+1} < p)\mathbb{E}[\alpha(p - p_{t+1})|p_{t+1} < p]$, *then all consumers will choose not to wait.*

PROOF: Take a consumer who wants to purchase today, that is, $\varepsilon_0 < \beta - \alpha p + \varepsilon_1$. Then there exists a $\overline{p} > p$ such that $\varepsilon_0 = \beta - \alpha\overline{p} + \varepsilon_1$. The expected gain for this consumer waiting comes from prices dropping below $p_t$ and from price increases up to the indifference point. If prices increase past $\overline{p}$, then $\varepsilon_0$ is preferred and there is no gain. Hence, the expected gains from waiting are

$$\begin{aligned}&\Pr(p_{t+1} < p)\mathbb{E}\big[\alpha(p - p_{t+1})|p_{t+1} < p\big]\\&\quad + \Pr(p < p_{t-1} \leq \overline{p})\mathbb{E}\big[\alpha(p - p_{t+1})|p < p_{t+1} \leq \overline{p}\big] - \overline{\phi}.\end{aligned}$$

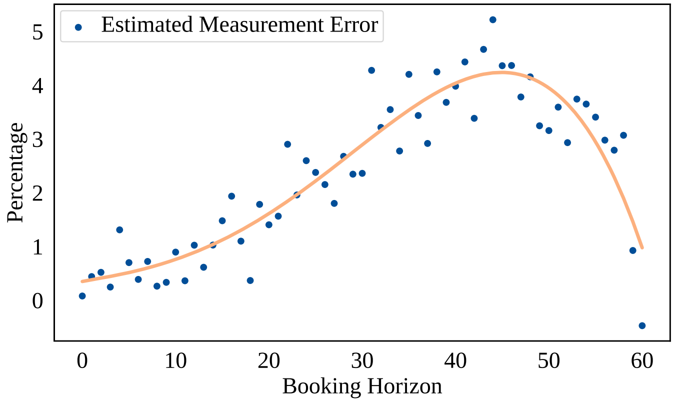


FIGURE 17.—Estimated seat map measurement error by day before departure. Note: Measurement error estimated by comparing seat maps with reported load factor using the United Airlines mobile website. The dots correspond to the daily mean, and the line corresponds to fitted values of an orthogonal polynomial regression of the fourth degree. Total sample size is equal to 15,567, with an average load factor of 70.7 percent.

TABLE IX

CONSUMER BUNCHING REGRESSIONS.

| | (1) | (2) | (3) |
|---|---|---|---|
| APD3 | −0.504 | −0.502 | −0.502 |
| | (0.144) | (0.142) | (0.142) |
| APD7 | 0.200 | 0.202 | 0.201 |
| | (0.0725) | (0.0697) | (0.0697) |
| APD14 | −0.0717 | −0.0720 | −0.0719 |
| | (0.0459) | (0.0414) | (0.0413) |
| APD21 | −0.131 | −0.131 | −0.130 |
| | (0.0412) | (0.0397) | (0.0397) |
| $m(t)$ | Yes | Yes | Yes |
| OD FE | Yes | Yes | – |
| Month FE | Yes | Yes | – |
| D.o.W. Search FE | No | Yes | Yes |
| D.o.W. Departure FE | No | Yes | – |
| Flight FE | No | No | Yes |
| Observations | 738,625 | 738,625 | 738,625 |
| $R^2$ | 0.609 | 0.618 | 0.748 |

*Note*: $m(t)$ is a sixth-order polynomial in days before departure, D.o.W. stands for day-of-week indicators for the day the flight leaves and the day of search. OD-Month clustered standard errors in parentheses.

The first term above is equal to $\overline{\phi}$, and the second term is less than or equal to zero. Hence, waiting is not optimal for a consumer wishing to buy today.

Next, consider a consumer who prefers not to buy a ticket today, that is, $\varepsilon_0 > \beta - \alpha p + \varepsilon_1$. Then there exists a $\underline{p} < p$ such that $\varepsilon_0 = \beta - \alpha \underline{p} + \varepsilon_1$. The gains from waiting come from price declines lower than the cutoff, and are equal to

$$\Pr(p_{t+1} < \underline{p})\mathbb{E}[\beta - \alpha p_{t+1} + \varepsilon_1 - \varepsilon_0 | p_{t+1} < \underline{p}] - \overline{\phi}.$$

Applying the definition of $\overline{\phi}$, this is equivalent to

$$\Pr(p_{t+1} < \underline{p})\mathbb{E}[\beta - \alpha p_{t+1} + \varepsilon_1 - \varepsilon_0 | p_{t+1} < \underline{p}] - \Pr(p_{t+1} < p)\mathbb{E}\big[\alpha(p - p_{t+1}) | p_{t+1} < p\big].$$

Define EG to be the expression above. Since $\underline{p} \leq p$, we have

$$\begin{aligned} \text{EG} &\leq \Pr(p_{t+1} < p)\big(\mathbb{E}[\beta - \alpha p_{t+1} + \varepsilon_1 - \varepsilon_0 | p_{t+1} < \underline{p}] - \mathbb{E}\big[\alpha(p - p_{t+1}) | p_{t+1} < p\big]\big) \\ &\leq \Pr(p_{t+1} < p)\big(\mathbb{E}[\beta - \alpha p_{t+1} + \varepsilon_1 - \varepsilon_0 | p_{t+1} < \underline{p}] - \mathbb{E}\big[\alpha(p - p_{t+1}) | p_{t+1} < \underline{p}\big]\big). \end{aligned}$$

Moving the expectation operator, the last line above equals

$$\Pr(p_{t+1} < p)\mathbb{E}\big[\beta - \alpha p_{t+1} + \varepsilon_1 - \varepsilon_0 - \alpha(p - p_{t+1}) | p_{t+1} < \underline{p}\big],$$

which can be simplified to $\Pr(p_{t+1} < p)\Pr(p_{t+1} < \underline{p})(\beta - \alpha p + \varepsilon_1 - \varepsilon_0) \leq 0$, since $\beta - \alpha p + \varepsilon_1 - \varepsilon_0 < 0$ by assumption. Hence, waiting is not optimal for a consumer wishing to not buy today. *Q.E.D.*

For consumers who would purchase today, the gains from waiting are equal to $\overline{\phi}$, but there is an additional cost if prices rise. Hence, waiting is not optimal. For consumers who would prefer not to buy, the expected gains of waiting are negative.

In monetary terms, $\overline{\phi}/\alpha = \Pr(p_{t+1} < p)\mathbb{E}[(p - p_{t+1})|p_{t+1} < p]$ defines a transaction cost such that waiting is never optimal. For these costs to be calculated, the information set of consumers needs to be defined. I assume consumers form expectations given current prices and time, but they do not forecast the changes in number of seats remaining across time. This seems reasonable given that remaining capacity is not reported to consumers. With these assumptions, I find the median and mean transaction costs to be \$5.85 and \$5.75, respectively. These costs are based on the most extreme case—the consumer who is indifferent between purchasing today or delaying the decision.

## D.1. *Initial Capacity and Approaching Static Pricing*

I compute optimal dynamic prices and simulate outcomes for a wide range of initial capacity values in order to investigate how large initial capacity has to be in order for static pricing to be a reasonable approximation of the environment.

I demonstrate the counterfactual exercise in Figure 18. In the left panel, the horizontal axis is the initial capacity condition. The left vertical axis is the percentage change in sales from increasing the initial capacity constraint by 1. The right vertical axis plots total expected revenues by initial capacity. The (gray) vertical line depicts the average observed initial capacity. The (light orange) square denotes revenues with six fewer seats than the average (a row of a plane); the (orange) triangle denotes the minimum initial capacity such that pricing can be approximated by a static model (revenues are within 0.5 percent).

The right panel plots average prices over time for the three initial capacities just described. The dashed blue (triangle) line shows the limiting case, where dynamic prices correspond to static prices. If the firm starts with fewer initial seats, realizations of demand impact prices.

I repeat this exercise for all markets, then compare initial observed capacities to the calculated thresholds. I find that 31.9 percent of the observed flights can be approximated by static pricing.

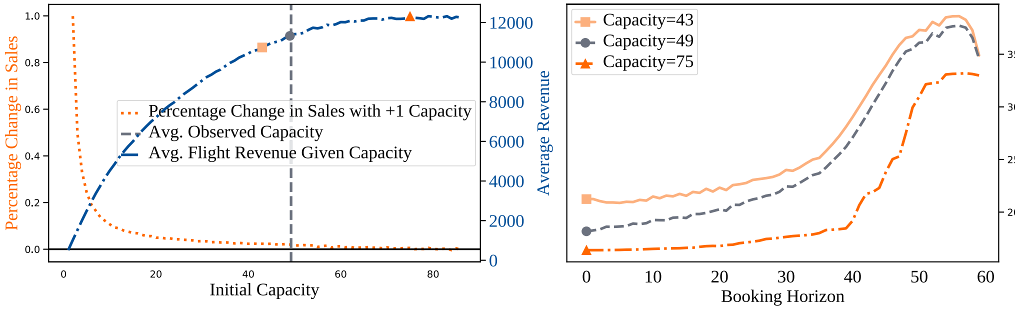


FIGURE 18.—Initial capacity counterfactual. Note: The left panel shows the percentage change in quantity sold by increasing the initial capacity constraint by 1 (dotted blue). Also shown are expected revenues by initial capacity constraint (dashed gray). The black vertical line shows the (weighted) average initial capacity observed in the data. The black dot shows expected revenues under this capacity. The gray square shows expected revenues with six fewer seats. The blue triangle shows expected revenues in the first instance when the percentage change in quantity sold is less than 0.5%. The right panel shows average prices over time for those three scenarios (average less ten, average, and the limiting case).

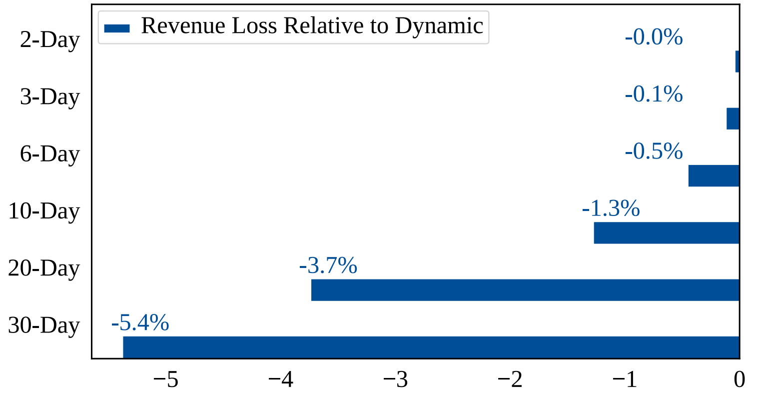


FIGURE 19.—The role of frequent price adjustments. Note: Revenue drop relative to dynamic (daily) pricing for all markets. For example, 3-Day corresponds to firms utilizing dynamic pricing, but restricting the number of price updates to 3-day intervals.

### D.2. *Frequent Price Adjustments*

I explore the use of dynamic pricing, with the restriction that prices are fixed for an interval of time ($k$ days). I conduct six counterfactuals, corresponding to $k = 2, 3, 6, 10, 20, 30$.

In Figure 19, I plot the revenue loss compared to daily re-optimization. I estimate that adjusting price once closes the revenue gap between dynamic pricing and uniform pricing by more than half (30-day adjustments). An additional price adjustment yields another 1.3 percent gain. Re-optimization with time intervals less than one week long results in similar revenues, meaning several demand shocks can be observed before re-optimization is required.

## REFERENCES

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