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Demand-shock characteristics and pricing behavior: A natural experiment from UEFA Euro 2016[☆]

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ABSTRACT

We consider a multi-period, limited capacity, unsegmented airline pricing model whose solution returns a sequence of increasing prices based on the order of sale. We show that a positive demand shock corresponding to an increase in the arrival rate reduces within-period price dispersion and has a minor impact on the sequence's maximum prices. Alternatively, upward shifts in customers' willingness-to-pay lead to higher maximum prices but do not affect within-period price dispersion. Demand shocks are identified in our sample by the draw that created the stage groups for the UEFA Euro 2016 soccer tournament. After the draw, some flights became suitable to transport foreign supporters to the location where matches were scheduled. Consistent with the theory, a different price behavior is observed between UK and continental European routes.

1. Introduction

On December 12th, 2015, an easyJet ticket for a London-Marseilles flight scheduled on June 11th, 2016 costed £109. Two days later, on December 14th, 2015, the price of the same ticket doubled to £221. Although there may be several possible economic explanations for such a price hike, in this paper we show that it is due to the demand shock associated to a large sport event that various French cities hosted during June–July 2016.

Indeed, on December 12th, 2015 the draw that created the stage groups of the 'UEFA Euro 2016' soccer tournament took place. Following the draw, England became one of the teams playing the match scheduled in Marseilles on June 11th, 2016. Therefore, England supporters learnt that they could now use the London-Marseilles flight as a suitable means of transport to reach the stadium.

This example shows that an exogenous shock (the draw) can modify the firm's (easyJet's) set of information on consumers' preferences and expected demand for a specific product (the flight), and the firm, taking into account such a change in the product's demand conditions, adjusts its price accordingly. However, following Alderighi et al. (2022) the subsequent analysis goes beyond the mere identification of a single price change. When a firm faces uncertain demand and has to sell multiple but limited units of inventory, we show that the shock leads to a variation of all units' prices.

In this paper, we extend the monopolistic multi-period pricing rule of multiple perishable units to obtain in each period a sequence of increasing prices in the units' order of sale; investigating the shape of the sequence before and after the shock provides a methodology to detect the nature of the shock.

Our theoretical model shows that a demand shock can consist in two, possibly coexisting, effects: a change in the customers' willingness-to-pay (WTP) and a change in their number (NUM). The underpinning idea is that the maximum price of the sequence and its dispersion are differently affected by the nature of the shock: a shift in WTP increases the maximum price and not the dispersion of the entire sequence; a shift in NUM reduces the dispersion and has a minor impact on the maximum price.

These two theoretical predictions are employed to investigate the airline price behavior during the European soccer tournament 'UEFA Euro 2016'. This tournament represents the world's third largest sport event, which attracts a very large number of supporters traveling to the

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[1] See www.uefa.com/MultimediaFiles/Download/Regulations/uefa/Others/84/03/26/840326_DOWNLOAD.pdf.

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cities hosting the soccer matches from all over Europe and beyond.[1] Therefore, the impact on the transport industry is relevant, especially, in this case, on airlines serving France, the country which hosted the tournament.

Amongst the airlines operating short-haul nonstop flights to France, we considered easyJet, one of the leading low-cost carriers in Europe. Starting from November 2015 onward, we collected daily the fares of several easyJet's flights linking different European countries with France during the month of June 2016, when the tournament took place.

Our empirical analysis focuses on the group-stage of the tournament, which was outlined by the draw on December 12th, 2015 in Paris. Because our data collection started on the first day of November 2015, we can observe the evolution of the airline fares in the pre-draw and in the post-draw period. We adopt a Difference-in-Difference (DID) approach to study how easyJet responded to the demand shock triggered by the draw.

We find that before the draw the price sequence of the flights affected by the shock (our treated sample) is similar to the price sequence of the same flights operated on days when no game is scheduled (our control sample). On the days that follow the draw, the price sequences of the two groups of flights drastically change: all units' prices of the treated flights are lifted up in response to the demand shock, while the prices of the control flights, which are not subject to the shock, remain approximately unaltered.

The fare intervention on the treated flights is, however, heterogeneous across routes. After the draw, the price sequence of the flights from the United Kingdom (UK) to France jumps up but flattens out, whereas the price sequence of the treated flights connecting three neighboring countries (Belgium, Italy and Switzerland, heretofore denoted as 3N) does not present a significant reduction in price dispersion and its maximum price shows a much more limited increase. Linking these findings to our theoretical model, the UK flights exhibit an increase in both WTP and NUM whereas the 3N flights are mainly subject to a raise of WTP.

Our analysis over the booking period reveals further interesting insights. In late spring, when the majority of soccer supporters have most likely purchased their tickets, the price sequence of the treated flights regains its usual increasing shape, which implies the return to a higher extent of price dispersion in a similar way as we observed during the pre-draw period. Finally, in the proximity of the departure date, when only few seats remain on sale, price dispersion decreases again because the available seats belong to very few fare classes (Alderighi et al., 2015; Hortacsu et al., 2024).

Our study is closely related to three main streams of literature. First, some recent empirical studies show that observed pricing rules adopted in the airlines industry differ from the empirical literature that studies pricing within frictionless models of a fully rational firm (see, *inter alios*, Aryal et al., 2023 and Williams, 2022). Alderighi et al. (2022) and Piga and Alderighi (2024) develop a multi-period revenue management model where firms cannot adjust prices instantaneously due to organizational frictions and technological bottlenecks, e.g., in accessing distribution channels. The outcome of the model is a rule that assigns a price to each unit of inventory, that is, the sequence of prices that this study also focuses on. In Alderighi et al. (2022) the use of sequences is independent of the market structure, while Piga and Alderighi (2024) emphasizes the stability over time of the sequences. Hortacsu et al. (2024) document, using data and operational insights from a large U.S. airline, the systematic use of a pricing heuristic that relies on inputs provided by different organizational departments; such a practice leaves room for possible miscoordination whose costs are counterbalanced by the relative simplicity and low computational burden of the adopted heuristic, known as the Expected Marginal Seat Revenue-b (Belobaba, 2009; Phillips, 2005).

Second, from a theoretical viewpoint, under conditions that typically characterize the airline market, namely demand uncertainty, limited capacity, and product perishability, Dana (1999) derives a single-period equilibrium in distribution that is qualitatively similar to the price sequences in this study: every capacity unit is assigned a price that increases in the order of sale. In addition to providing an empirical representation of the fare sequences, this study differs from Dana (1999) as it proposes a multi-period theoretical model that explicitly deals with two opposing forces on prices: the positive effect due to capacity scarcity vs. the negative one induced by capacity perishability, which becomes stronger as the reservation period nears its end.[2] Alderighi et al. (2015), using standard regression methods on European airline data that include the number of seats available when a price was posted online, test and find support for the main prediction in Dana (1999). Both theoretical and empirical considerations thus suggest that when it is not possible to control for capacity effects, a mere increase in fares over time cannot be automatically ascribed to an intertemporal price discrimination motive, which operates as another upward force on prices (see Siegert and Ulbricht, 2020 for an example). By the same token, previous studies on price dispersion in airline markets have largely focused on its relationship with market structure that only indirectly captures the impact of capacity (Borenstein and Rose, 1994; Gaggero and Piga, 2011; Gerardi and Shapiro, 2009). This study proposes a complementary source of intra-firm price dispersion that is directly related to the way the company manages the price sequences over time. The theoretical mechanism we present thus sheds some light on the empirical findings in Orlov (2011) that reports an increase in intra-firm dispersion after the Internet became a crucial distribution system.

Third, there are various instances and different industries showing that firms respond to a demand shock.[3] Gagnon and López-Salido (2020) show that large demand shocks caused by mass population displacement, snowstorms and hurricanes trigger a negative, but weak, price response in U.S. supermarkets. A weak price response to negative demand shocks has been also documented in airline transport (Bilotkach et al., 2012). In the same industry, Gaggero and Luttmann (2022) find that major U.S. carriers responded to COVID-19 by discounting fares and decreasing the price dispersion, while in a study on the modal competition of high-speed rail versus air transport, Wei et al. (2017) find that demand shocks have a larger impact on low-cost or regional carriers, on tourism routes, and on flights that depart in the evening. Berman et al. (2019) show that young exporters respond to a demand shock more intensively than more established firms. Baker (1989) and Menezes and Quiggin (2022) relate the intensity of the reply to the level of market power, showing that price response to inflationary demand shocks is larger in more concentrated markets. Kwapil et al. (2010), however, find an opposite result.

Another key aspect of the firm's reply to demand shocks is the speed of adjustment, which can be affected by market rigidities as well as by the availability of the information (Hall and Fields, 1987). Balvers and Cosimano (1990) show that a firm with no clear information on the size of the shock may prefer to slowly adjust its prices to avoid the risk of inducing additional noise which may ultimately obstruct the learning process. In another study based on the EURO16 event, Nicolini et al. (2023) find that hotel prices were largely unresponsive to the draw on

[2] Dana (1999) considers only the capacity effect. Both studies assume pre-commitment of the solution strategy.

[3] In some industries the price adjustment is not the main consequence of a demand shock. For example, Copeland and Hall (2011) show that in the short-run car producers only modestly respond with changes in price since they prefer to raise/lower the level of production or allow inventories to accumulate/decumulate. With respect to the inventory decisions, Tokar et al. (2014) find that managers tend to overreact when they are faced with the uncertainty of demand shocks. Demand shocks may affect the entry and exit decision of firms (Lim et al., 2022); their productivity and trading decisions (Bai and Ríos-Rull, 2015); and their investment decision (Angeletos and Lian, 2022).

December 12th, 2015; they show that Paris hotels initially applied the same room rates on the dates when matches were scheduled and that this price uniformity broke down to reflect differing occupancy rate on those dates. The present study highlights the company's ability to alter its pricing rules selectively on those routes directly affected by the demand shock, although the extent and the speed of its intervention varies by routes' characteristics.

This paper continues as follows. The next section presents a theoretical model of airline pricing and shows how a monopolistic airline reacts to a demand shock. Then, the paper tests the theoretical insights. Section 3 illustrates the data collection process and the main sample characteristics. A brief descriptive analysis is presented in Section 4, which paves the way for the subsequent analysis that, in Section 5 describes the econometric model and in Section 6 discusses the results. Section 7 concludes.

2. Pricing under demand shocks

This section extends the model presented in Alderighi et al. (2022) by accounting for a demand shock consisting in an unexpected upward shift of both the prospective number of consumers (NUM) and their willingness to pay (WTP). To fit the empirical applications, the model refers to the airline market, although the setup is sufficiently general to be applicable in many other industries adopting revenue management practices (e.g., hotel, car rental, train, long-distance bus, entertainment and sports).

A monopolistic airline sets fares for a flight with capacity of $N > 1$ homogeneous seats over $T \geq 1$ periods before departure. Let t identify the remaining number of periods to departure, with $T \geq t \geq 1$, and $t = 0$ the take-off day. At each t, consumers $h = 1, 2, \ldots, \infty$ arrive sequentially: the probability that at t the first consumer shows up is $\varphi_{1,t} \in (0, 1)$, and that consumer $h+1$ shows up, conditional on the fact that consumer h has already appeared, is $\varphi_{h+1,t} \in (0, 1)$. The arrival process (i.e., NUM) within the same time period is memoryless, i.e., for any h and t, $\varphi_{h,t} = \varphi_t \in (0, 1)$, and the conditional probability of arrivals may increase over time, i.e., $\varphi_{t'} \geq \varphi_t$ with $t' < t$.

Consumer (h, t) is myopic with a WTP denoted by a random variable $\theta_{h,t}$, with (right-continuous) cumulative distribution $F_{h,t}$ on the support Θ, with $\underline{\theta} = \inf \Theta > 0$ and $\bar{\theta} = \sup \Theta < \infty$.[4] Moreover, consumers arriving at the same time period t share the same ex-ante evaluation, $F_{h,t} = F_t$, and consumers arriving later may have higher WTP, i.e., $F_{t'} \leq F_t$ with $t' < t$.

The probability of selling the first available seat at the fare p at time period t is:

$$q_t(p) = \varphi_t \left(1 - F_t(p)\right) \sum_{h=0}^{\infty} \left(\varphi_t F_t(p)\right)^h = \frac{\varphi_t \left(1 - F_t(p)\right)}{1 - \varphi_t F_t(p)} \in [0, 1], \tag{1}$$

where $\varphi_t \left(1 - F_t(p)\right)$ is the probability that consumer h shows up and buys at fare p in time period t, provided that consumers $1, \ldots, h-1$ have previously not purchased at the same price in the same time period; and $\left(\varphi_t F_t(p)\right)^h$ is the probability that consumers 1 to h showed up and did not buy in time period t.

The following Bellman equation summarizes the firm's revenue maximization problem:

$$\begin{aligned} V(t, M) = \max_{p \in \Theta} \{ & q_t(p) [p + V(t, M-1)] \\ & + \left(1 - q_t(p)\right) V(t-1, M) \}, \end{aligned} \tag{2}$$

with boundary conditions $V(t, 0) = 0$ and $V(0, M) = 0$, for any $t \in \{0, \ldots, T\}$ and $M \in \{0, \ldots, N\}$.

Eq. (2) encompasses the trade-off of either selling at least one seat at time t and gaining p plus the revenue flow stemming from the remaining seats, $V(t, M-1)$, or freezing the capacity and postponing the entire sale to the next time period, which implies gaining $V(t-1, M)$.

The solution to the model determines, in any period, a sequence of ascending fares based on the order in which each seat is sold (see Proposition 2 in Alderighi et al., 2022). Since in the present paper we consider a more general setup than in Alderighi et al. (2022) (i.e., WTP and NUM may be increasing over time), the optimal fare for each seat over the booking period is no more strictly monotonic.

Because q_t depends on the WTP and NUM in each booking period (F_t and φ_t, respectively), the model can shed light on how a demand shock (i.e., a variation in such variables) affects the shape of the optimal fare sequence.

We focus our attention to an expected shock occurring at period $t = T \in \{1, \bar{T}\}$ and we evaluate how prices modify from this period onward, i.e., $T, T-1, \ldots, 2, 1$. Indeed, as the shock unfolds only in T, the set of optimal fares before T, i.e. $\{p_{t,m} \mid T+1 \leq t \leq \bar{T}, 1 \geq m \geq \bar{M}\}$, remains unchanged. In Proposition 1, we, therefore, limit our analysis to the set of fares which could be potentially affected by the shock.

Proposition 1. *Let F be a continuously differentiable and bounded function with support $\Theta = [\underline{\theta}, \bar{\theta}]$, with $0 \leq \underline{\theta} < \bar{\theta} < \infty$. Assume that $t \in \{0, 1, 2, \ldots, T-1, T\}$; $m \in \{0, 1, 2, \ldots, M-1, M\}$, with $T > 1$ and $M > 1$; and that the unexpected positive demand shock occurs at time T. Define the optimal price of seat m at time t as $p_{t,m}$; the sequence of optimal prices of length $m \leq M$ at time $t \leq T$ as $S_{t,m} = \{p_{t,m}, p_{t,m-1}, \ldots, p_{t,1}\}$; and the coefficient of variation of the optimal price sequence $S_{t,m}$ as $CV_{t,m} = \sigma_{t,m}/\mu_{t,m}$, where $\sigma_{t,m}$ and $\mu_{t,m}$ are, respectively, the standard deviation and the mean of the optimal sequence of prices $S_{t,m}$. Let tilde ("˜") denote the same variables after the shock at time T.*

A. *If a positive and unexpected shock in WTP occurs, i.e., $\tilde{F}(x) = F(x/\alpha)$, with $\alpha > 1$, then $\tilde{p}_{t,m} = \alpha p_{t,m} > p_{t,m}$ and $\widetilde{CV}_{t,m} = CV_{t,m}$;*
B. *if a positive and unexpected shock in NUM occurs, i.e., $\tilde{\varphi} = \beta\varphi$, with $\beta > 1$ and $\tilde{\varphi} \leq 1$, then under mild conditions, $\tilde{p}_{t,m} \geq p_{t,m}$;*
C. *if a positive and unexpected shock in NUM occurs, i.e., $\tilde{\varphi} = \beta\varphi$, with $\beta > 1$, $\tilde{\varphi} \leq 1$, and φ and/or β are sufficiently large, for any t and m, $\tilde{p}_{t,1}/p_{t,1} < \tilde{p}_{t,m}/p_{t,m}$ and $\widetilde{CV}_{t,m} < CV_{t,m}$.*

Proof. See Appendix A.1. ■

An increase in WTP, therefore, determines a proportional shift of all prices of the sequence upward and no change in fare dispersion, whereas an increase in NUM has larger effects on the lower prices of the sequence and lower effects on the higher prices of the sequence, leading to a reduction in dispersion.

These results are illustrated in Fig. 1, with panel (a) containing the baseline case with stable demand, which provides the term of reference for the other panels in the Figure.[5] Panels (b)–(d) describe how a change in, respectively, NUM, WTP or both can affect the sequence of fares. We split the booking period in two stages: an early stage, denoted by $t \in \{5, \ldots, 8\}$, where demand is stable and a late stage, denoted by $t \in \{1, \ldots, 4\}$, where a positive demand shock occurs.[6]

[4] This assumption guarantees the existence of a solution of the problem. Moreover, note that the random variable $\theta_{h,t}$ can be one of continuous, discrete or mixed type.

[5] In the baseline case: $N = 20$, $t = \{1, \ldots, 8\}$, $F_t(p) = \min\{80(1.1228 - 0.04t)/p, 1\}$, $\varphi_t = 0.85 - 0.005t$. Hence, the expected average demand, Q, is linear and equal to $Q = 40 - 0.5p$, implying that the quantity is 20 and the price is 40 where the demand elasticity is unitary. Expected demand increases by 4 percent in WTP and NUM in each time period (time index is in the reverse order) to better reflect the fact that in airline markets travelers with higher willingness to pay tend to book later.

[6] In the early stage, consumers' average arrival rate is $\hat{\varphi} = 0.83$ and $F_t(p) = \min\{80(1.1228 - 0.04t)/p, 1\}$. In the late stage, either the expected number of arrivals (NUM) increases to $\hat{\varphi} = 0.91$ or the willingness-to-pay (WTP) shifts

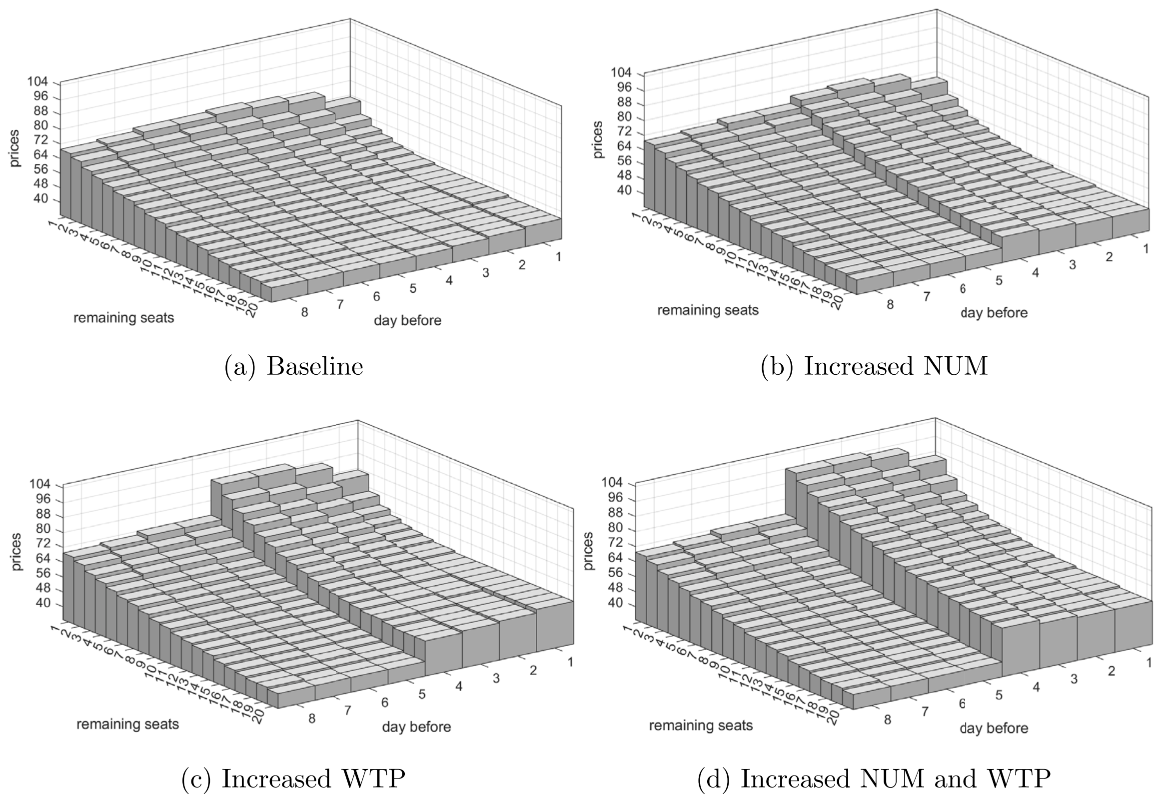


Fig. 1. Simulated fare sequence, with and without demand shocks.

Note that an increase in NUM has a major effect on lower fares, while an increase in WTP has a uniform effect on all fares. Finally, the overall effect amplifies when both shocks occur simultaneously.

Fig. 2 shows the impact of a change in the expected number of arrival (NUM) and in their willingness to pay (WTP) on the minimum price ($\underline{p}$), maximum price ($\bar{p}$) and coefficient of variation (CV_t).[7] It clearly depicts the main results in Proposition 1 in terms of how different shocks impact on the distribution of fares. In particular, a change in WTP has no effects on the coefficient of variation, whereas a change in NUM increases the minimum fare proportionately more than the maximum fare and thus reduces the coefficient of variation.

3. Data collection and sample characteristics

As in Alderighi et al. (2022), data were scraped from the internet using a web crawler. On a daily basis, the crawler automatically connected to the web site of easyJet and issued queries specifying the route, the date of departure, and the number of seats to be booked. The data collection explicitly aimed at recovering the fare sequence of each flight stored on the carrier's web reservation system. To this purpose, for each flight and departure date, the crawler started by requesting the price of one seat, and then continued by sequentially increasing the number of seats by one unit. The query stopped at 40 seats, which corresponds to the largest possible number within a single query, or at a smaller number of seats if the remaining seats on sale were less than 40.

To select the flights, the following French airports were chosen as they are located in the same cities hosting matches and easyJet was operative: Bordeaux, Nice, Lille, Lyon, Nantes, Paris CDG and Toulouse. The data collection covers 28 bi-directional routes, of which 6 domestic and 22 international, linking the French airports with 12 European nations.[8] Most of the fares were retrieved in Euro and the non-Euro fares were converted to Euro using the daily exchange rate provided by Eurostat.[9]

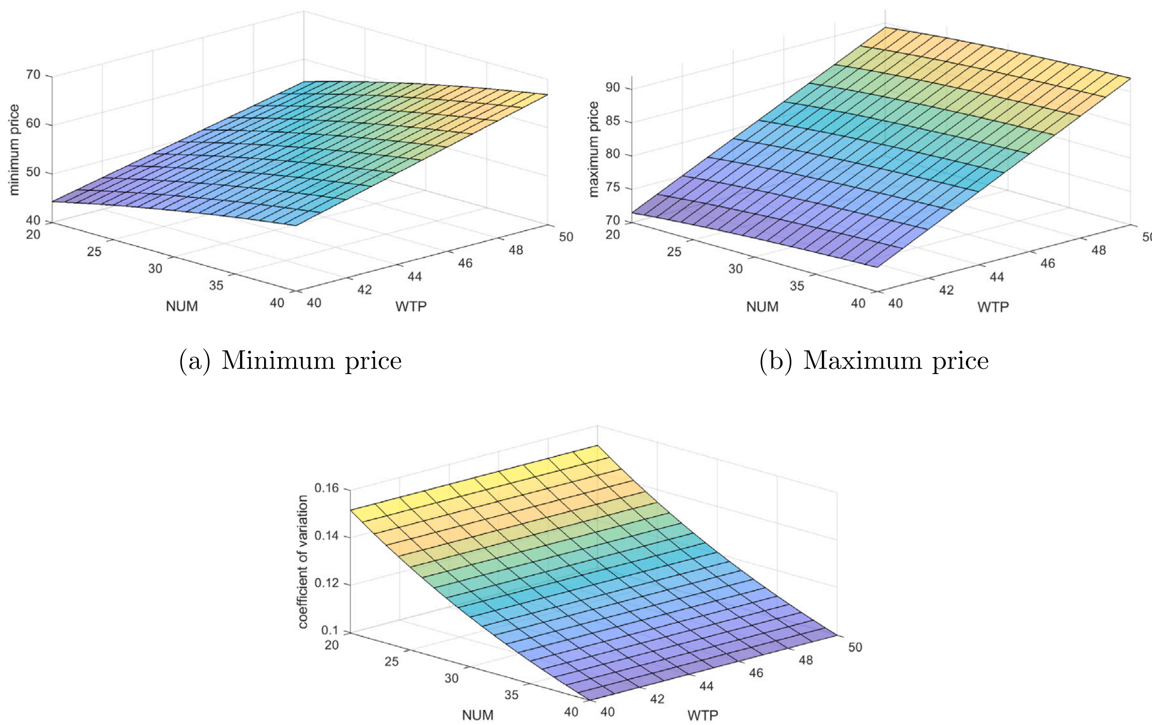
The sampled flights departed within the dates June 1th and June 24th, 2016: as the first match was played on June 10th, the sample therefore includes a pre-tournament period. The fare collection started on November 1th, 2015, approximately seven and a half months before the beginning of tournament, and forty-two days before the draw on December 12th, 2015 that determined the identity of the teams playing in each city. Overall, we tracked a total of 546 flights until their departure date, or earlier if the flight sold out. It is thus possible to construct a sample containing both flights which could be potentially

upward to $F_t(p) = \min\{100(1.1228 - 0.04t)/p, 1\}$ or both. Each case thus denotes a linear demand with, respectively, quantity equal to 40 and 20 and price to 40 and 50, where the demand elasticity is unitary.

[7] We use the same parameters of Fig. 1. We focus on the sequence of fares at time $t = 4$. The changes in NUM and WTP correspond, respectively, to a positive shift in the expected number of travelers from 20 to 40 and in their maximum willingness-to-pay from 40 to 50, where the demand elasticity is unitary.

[8] **Routes**: Amsterdam-Nice, Belfast-Bordeaux, Belfast-Paris(CDG), Belfast-Nice, Berlin(SXF)-Nice, Bordeaux-Lille, Bordeaux-Lyon, Brussels-Bordeaux, Brussels-Nice, Budapest-Paris(CDG), Budapest-Geneva, Geneva-Lille, Hamburg-Nice, Lille-Nice, Lille-Toulouse, Lisbon-Lille, Lisbon-Paris(CDG), London(LGW)-Lyon, London(LGW)-Marseille, London(LGW)-Paris(CDG), London(STN)-Nice, Lyon-Nantes, Madrid-Lyon, Madrid-Paris(CDG), Naples-Lyon, Paris(ORY)-Toulouse, Prague-Paris(CDG), and Rome(FCO)-Lyon. **Nations**: Belgium, Czech Republic, Germany, Hungary, Italy, Netherlands, Northern Ireland, Portugal, Spain, Switzerland, England and Northern Ireland, of which only the Netherlands did not participate in the tournament.

[9] We used the series 'Former euro area national currencies vs. euro/ECU' downloaded from https://ec.europa.eu/eurostat/web/exchange-and-interest-rates/data/database. The missing data on weekends or national holidays, when financial markets are closed, are filled with the previously available observation. The non-Euro currencies of our sample are the British Pound, the Czech Crown, the Hungarian Forint, and the Swiss Franc.



(a) Minimum price

(b) Maximum price

(c) Coefficient of variation

Fig. 2. Minimum price, maximum price, and coefficient of variation as a function of NUM and WTP.

used by supporters to attend a match involving their national team and flights that were not affected by the tournament. A flight is classified as 'treated' if it links a foreign country to the French host city within a −/+ two-day range from the date of the soccer match involving that country. More specifically, we take incoming flights from two preceding days until the day of the match, and the next two days after the match for the return flight.[10]

Table 1 reports the matches with the corresponding routes of the flights included in the treatment group. These flights are associated with nine group-stage soccer matches, which involve the national teams of three neighboring countries of France (Belgium, Italy and Switzerland), henceforth referred as 3N, and two national teams from the United Kingdom (England and Northern Ireland), henceforth referred as UK.

As we focus on the group-stage of the tournament, the sample includes 52 treated flights for a total of 8,464 observations. Note that the selected matches are played between June 11th and June 22th, meaning that all the treated flights depart within the same narrow period of less than a fortnight length. This feature ensures that these flights are subject to the same, if any, seasonal effect.

Another reason to consider the group-stage of the tournament is the fact that the draw pairing the qualified teams and designating the group-stage matches took place on December 12th, 2015. Since the tournament started on June 10th, 2016, the demand shock due to UEFA Euro 2016 occurs six months before the flights' departure; that time represents a stage of the booking period when fares are usually very stable across subsequent booking days, so that we can most likely ascribe any fare variation to the sole effect of the demand shock induced by the draw (see also Nicolini et al., 2023 for hotel prices). To put it differently, the draw did not occur in the late booking period, when fares typically soar simply because of intertemporal price discrimination (Alderighi et al., 2016), so with our data we are able to confine the effect of the demand shock when we expect nothing else to happen, and any fare change that we observe after December 12th, 2015 is arguably attributable to the group-stage draw.

As far as the control group is concerned, the richness of our data allows us to consider two alternatives. The first possibility is to take the same flight code of each treated flight and select the flight that departs one week earlier than the treated flight. We will refer to this alternative as the 'previous-week' control group, or simply, previous-week group. One advantage of this group is to pair (and compare) flights that exactly share the same features in terms of origin and destination, departure and arrival time, day of the week of departure, season of the year, etc., except for the departure date, which, however, is only seven-day distant from the other.[11]

The second alternative for the control group is to consider all the flights in our dataset that takeoff before the beginning of the tournament, or, more precisely, before June 9th, when our first treated flight is observed. For the sake of the exposition, we will refer to this control group as 'pre-tournament' group. It is worth mentioning that this control group is based on flights which serve *all* the 28 routes of our collected sample. As we stated earlier, these routes are both domestic and international, and cover a total of 12 European countries including France (see footnote 3). In this way, the pre-tournament group represents an overall and broad group of flights aiming to reflect the general pricing strategy of easyJet under normal condition. Again, since the pre-tournament group includes flights departing within the period June 1th and June 8th, any seasonality effect on fares, if it exists, will be the same across all flights.

[10] On the day of the soccer match the incoming flight is considered treated if its scheduled landing time is no later than 5 h before the beginning of the soccer match to allow the supporters enough time to reach the stadium before the kick-off.

[11] This idea is consistent with Alderighi et al. (2015) and Bilotkach et al. (2015) who used past-week flights to instrument current flights.

Table 1
Sampled group-stage games with corresponding routes and national teams.

Date of match	Group-stage game	Route	National team	Cluster
June 11th, 2016	Albania-Switzerland	Geneva-Lille	Switzerland	3N
June 11th, 2016	England-Russia	London(LGW)-Marseille	England	UK
June 12th, 2016	Poland-Northern Ireland	Belfast-Nice	Northern Ireland	UK
June 13th, 2016	Belgium-Italy	Naples-Lyon	Italy	3N
June 13th, 2016	Belgium-Italy	Rome(FCO)-Lyon	Italy	3N
June 18th, 2016	Belgium-Republic of Ireland	Brussels-Bordeaux	Belgium	3N
June 19th, 2016	Switzerland-France	Geneva-Lille	Switzerland	3N
June 20th, 2016	Slovakia-England	London(LGW)-Lyon	England	UK
June 21th, 2016	Northern Ireland-Germany	Belfast-Paris(CDG)	Northern Ireland	UK
June 22th, 2016	Sweden-Belgium	Brussels-Nice	Belgium	3N

The two aforementioned alternatives for the control group have their own pros and cons. On the one hand, the previous-week group satisfies an important requirement for the choice of the counterfactual sample, since each treated flight is matched with its same flight service offered one week before. On the other hand, the pre-tournament group offers a more generalized term of comparison as it captures the pricing approach adopted by easyJet over a wider portion of its network. Indeed, whereas the previous-week group includes 6,968 observations, the size of the pre-tournament sample is almost nine times bigger (61,339 observations). We present evidence using both samples. The main analysis of this paper will be conducted using the previous-week flights as control group, while the robustness checks will be based on the pre-tournament flights.

4. Descriptive analysis

Fig. 3 shows the box plot of the fare sequence of four different flights. Each box shows the minimum, the 25th percentile $Pc25$, the median (the internal horizontal line), the 75th percentile $Pc75$ and the maximum price of the sequence posted on each day of December 2015, with the vertical dashed line denoting the day of the draw. Finally, the solid line represents the coefficient of variation, computed as the standard error of the fare sequence divided by its mean.

The two left panels in Fig. 3 depict two treated flights: the one on top is from the United Kingdom (UK-route cluster); the bottom one from Belgium (3N-route cluster); the right panels refer to the two corresponding flights from the previous-week control group.

Prior to the draw, the interquartile range (i.e., the distance between the 75th and 25th percentiles), which is denoted by the height of the gray boxes, is observable in all the panels, implying that *all* four flights were priced using an ample range of fare classes.

After the draw, we observe two different effects on the treated flights. The interquartile boxes of the UK flight quickly disappear, as the fare sequence collapses and all seats are assigned to two or three fare classes of higher level than before. By contrast, the interquartile boxes of the 3N flight are maintained but shifted up. The coefficient of variation, which represents a measure of fare dispersion, reduces in both treated flights, but the drop is drastically larger for the UK one. It is noteworthy that the fare sequences of the control flights do not exhibit any change after the draw.

Based on the predictions of the theoretical model, we can interpret these graphical findings as follows: after the draw, the airline anticipated an increase in both WTP and NUM for the UK flight, whereas for the 3N flight only an increase in WTP, but no drastic increase in the number of consumers. This could be due to the fact that Belgian supporters could substitute flights with alternative means of land transport, an option not available to British travelers.

Last, but not least, it is worth pointing out that the fare adjustment did not occur exactly on the day after the draw; moreover, it was not even simultaneous across all the treated flights. Although Fig. 3 only considers two flights, it well generalizes the behavior of the treated flights in our sample: some flights were updated on December 14th, 2015, whereas for others the fare sequence change took longer to manifest. Hortacsu et al. (2024) provide a possible explanation based on organizational frictions. Note that the draw was held in Paris on Saturday, December 12th, 2015 at 6 pm local time. It ended about a couple of hours later, when the Revenue Management (RM) office of easyJet was probably closed, and likely stayed so (or at least not fully operative) on the next day, Sunday. When normal working activities resumed on the Monday morning, Revenue Managers assigned a higher priority to the decision on how to adjust the fare sequences of the UK flights, likely because of their lower product substitutability. One possible reason why the airline did not devote more resources to implement changes over the weekend or soon thereafter is probably due the fact that only a small number of supporters would book a flight or a hotel room before securing a ticket for the entrance to the match's stadium (Nicolini et al., 2023).

5. Econometric model

We adopt a modified DID approach where, instead of splitting the time horizon into two categories of fares observed before and after the draw, a single dummy variable for each query date is used. More precisely:

$$Y_{it} = \sum_{t=1}^{n-1} \alpha_t QueryDate_t + \sum_{t=1}^{n-1} \beta_t (QueryDate_t \cdot Treated_i) + \rho_i + \epsilon_{it}. \quad (3)$$

Each of the *n-1* $QueryDate$ dummy variables represents a date of the fare query t, where n is the total number of daily observations collected for each flight i. The variable $Treated$ is a dichotomous variable equal to one if the flight i belongs to the treatment group and to zero otherwise. The interaction $Treated \cdot QueryDate$, therefore, takes the value one when the flight is treated and observed on a specific query date. The coefficients β's measure the average difference of the dependent variable between treated and control flights, on each query date. They should be positive and significant if the post-draw shock led to a modification of the fare sequence in treated flights only. Such a specification allows us to observe how the impact of the shock evolves over time, especially in the post-draw period when the effect of the shock may not remain constant over time. The estimation controls for flight fixed-effects ρ; ϵ is i.i.d. with zero mean.

To test that the shock impacts the entire fare sequence and not only the lowest available fare, the dependent variable Y_{it} for flight i at time t before departure assumes five alternative values: the lowest available fare, $Pmin$, corresponding to the first seat in the sequence for sale; the twenty-fifth percentile of the fare sequence, $Pc25$; the seventy-fifth percentile of the fare sequence, $Pc75$; the highest observable fare, $Pmax$; and the coefficient of variation of the observed fare sequence, CV, which is measured as the ratio between the standard deviation of the fares in the sequence and their mean value. Significant differences in values between the first four variables would indicate that the airline stored a fare sequence on its reservation site, i.e., that each seat is progressively assigned to an increasing fare class (Alderighi et al., 2022). The coefficient of variation measures instead how dispersed the fares in a sequence are. Finally, standard errors are clustered at flight level.

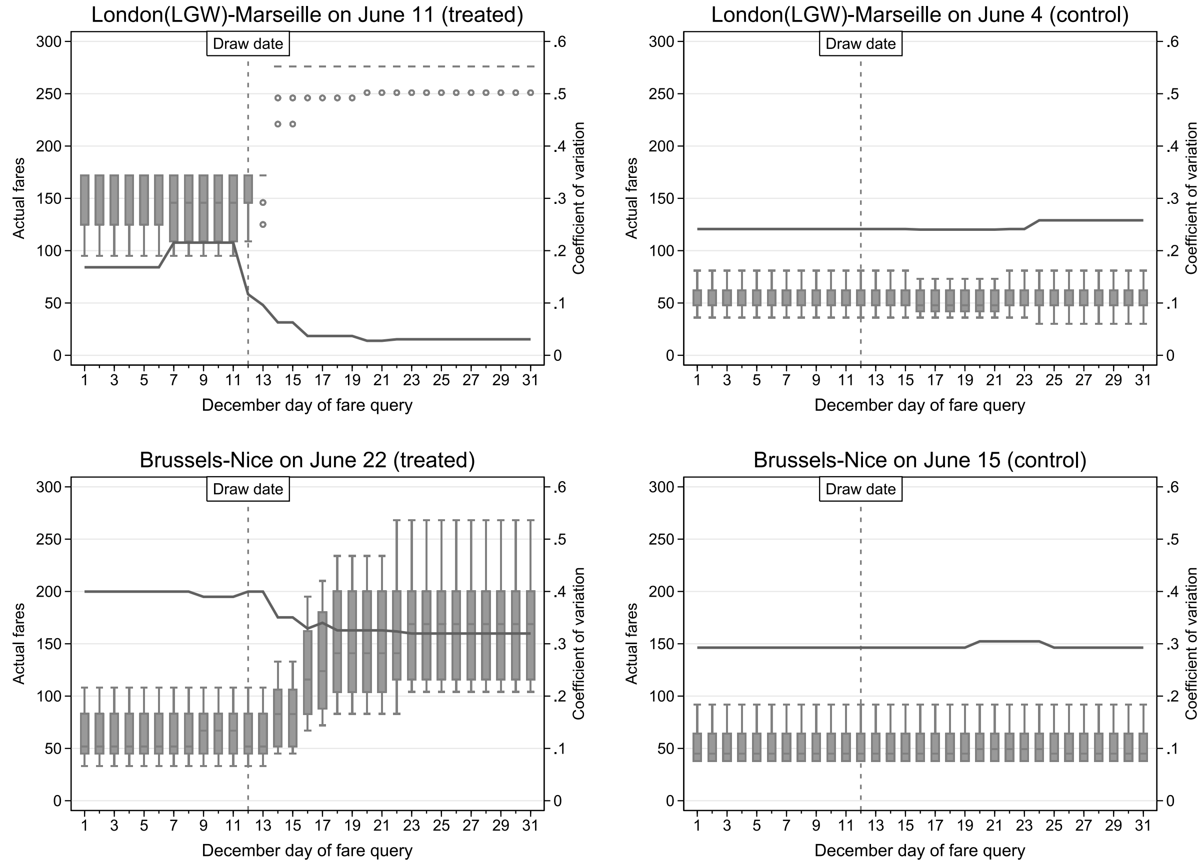


Fig. 3. Distribution of values (left vertical axis) and Coefficient of Variation (right vertical axis) of fares in observed sequences.

6. Results

Given the long time-horizon of our estimation (November 2015 to June 2016), the regressions we estimate include more than seven months of daily dummies $QueryDate$ and therefore reporting all the estimates in a table would be too complex and hard to read and interpret. For this reason, we opted for a graphical representation of the results obtained by calculating and plotting the predicted values of Eq. (3) - for a similar approach, see Lacetera et al. (2024).

6.1. Results immediately before and after the draw

Fig. 4 displays the predicted values of Eq. (3) obtained using the entire sample of control and treated flights. Both panels focus on the month of December 2015 to get a closer look at how the samples of treated and control flight behave just before and after the draw.

The left panel shows the predicted values of the four fare classes considered as dependent variables ($Pmin$, $Pc25$, $Pc75$, and $Pmax$); the right panel shows the predicted coefficient of variation. The values of the treated flights are represented by the solid lines, while the dotted lines refer to the control flights. In the left panel the same color is used to identify the same dependent variable in both samples; so, for example, the red color identifies $Pmax$. To enhance clarity, the figure does not show the confidence intervals, which are generally very small, and point towards significant differences among the curves.

Notice that during the pre-draw period the fares and the coefficient of variation of both the treated and the control flights follow a similar temporal pattern. Indeed, the solid and the dotted lines tend to overlap extensively. That is, before the draw the dependent variables not only move in parallel in both groups, but also take similar values (recall that the sample includes flights with the same identifying codes). Having established a common pre-shock trend, we can proceed to evaluate the impact of the shock induced by the draw on the treated flights.

The left panel of Fig. 4 point to the following results. First, all the fares of the treated flights jump up after the draw, whereas those of the control group continue to retain similar pre-shock values. For instance, $Pmin$ moves from an average value of about 60 in the pre-draw period to 150 just a few days after the draw. $Pc25$, $Pc75$, and $Pmax$ exhibit similar sharp increments. It appears, therefore, that the airline responded to the shock by shifting up the fare sequences of all treated flights.

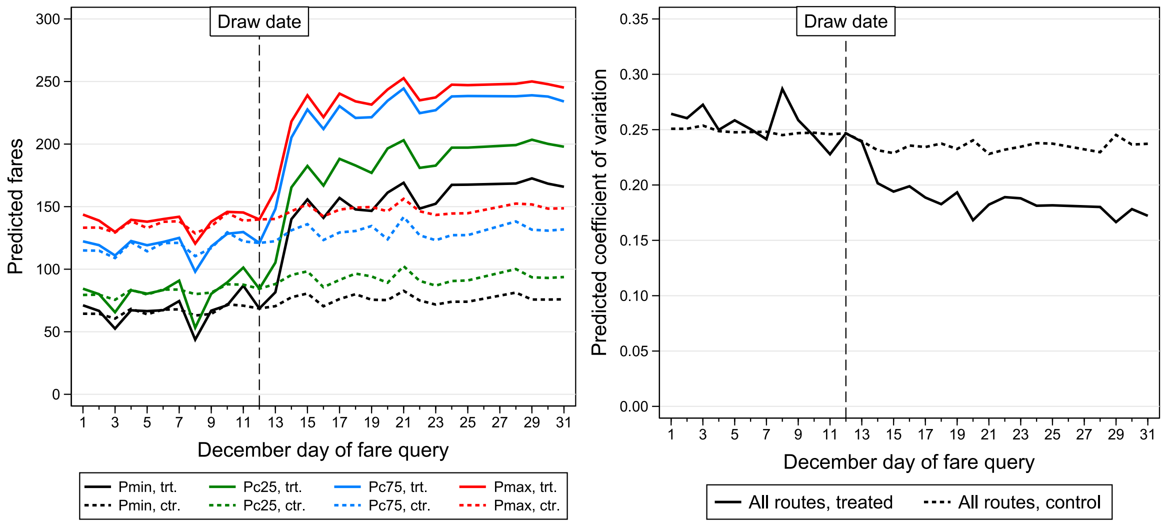
Second, such an adjustment was not instantaneous, but took a few days to complete. Indeed, the predicted prices the day after the draw tend to be similar to the preceding ones, and noticeable increment only appear on December 14th, 2015.

Third, the distance between $Pmin$ and $Pc25$ becomes wider after the draw, while the distance between $Pmax$ and $Pc75$ shrinks. This finding indicates that the fare sequence after the draw is skewed to the left, with more seats allocated to the highest fare classes. Moreover, the fact that the $Pc75$ curve is very close to the $Pmax$ curve suggests that more seats are assigned to a smaller number of higher fare classes, implying that the fare sequence distribution exhibit a thicker right tail. This result is consistent with the top-left panel of Fig. 3 shown previously.

Fourth, the fact that in the post-draw period the fare sequence is based on a limited number of fare classes determines a lower fare dispersion. This result is showed in the right panel of Fig. 4, where the average value of the coefficient of variation of the fare sequences in treated flights declines noticeably after the draw.

6.2. Results by subsamples

To capture possible differing patterns of travel mode substitutability, we split our sample in two groups: one comprising the flights linking France to the UK (UK routes) and another gathering the flights



(a) Predicted fares

(b) Predicted coefficient of variation

Fig. 4. Predicted fares and coefficient of variation in December 2015.

linking France to its three neighboring countries (3N routes) in mainland Europe. The former group of flights is characterized by a lower substitutability with other means of transport, which are more expensive and inconvenient for passengers from an island. Thus, it is likely that on UK routes the airline could enjoy a significant market power, leading to large price post-shock increments. Conversely, the 3N routes share a physical border with France and thus ground transportation represents a credible alternative to air transportation that may potentially limit the impact of the shock.

As the panels (a) and (c) of Fig. 5 show, fares were more reactive on the UK routes than on 3N routes. Although both samples exhibit significant shifts upward of all prices, they are much steeper on UK routes; moreover, after the draw $Pc75$ on UK routes approximately overlaps with $Pmax$, while $Pc25$ is equally distant from $Pc75$ and from $Pmin$, meaning that the fare sequence is very skewed to the left, with only few and high fare classes available.

Relatedly, the right panels show a quick and significant drop of the coefficient of variation only on the UK routes after the draw, while the coefficient of variation of the treated flights on 3N routes is more sluggish to fall and generally does not differ drastically in magnitude from that in the control sample. In terms of theoretical predictions in Proposition 1, these findings suggest that the UK routes of our sample experienced an increase in both WTP and NUM, whereas the 3N routes were mainly subject to an increase in WTP.

6.3. Results over the full booking period

The analysis so far has focused on the month of December 2015 to get a closer look at the airline's behavior just a few days before and after the draw. However adjustments of the fare sequences also occurred in the following months. Shifting the attention to the entire post-draw booking period, which is depicted in Fig. 6, reveals further interesting insights.

The pattern of the treated flights on UK routes after the draw broadly identifies three subperiods:

- subperiod A (draw-date to March 2016) where treated fare sequences rise after the draw and remain at the highest levels;
- subperiod B (April 2016 to early-May 2016) where fares tend to decline, although they remain at levels much higher than in the control group;
- subperiod C (mid-May 2016 to June 2016) where fares increase again.[12]

In contrast, on 3N routes during the subperiods A and B fares show an upward trend relative to the December-2015 period, which suggests that it took longer to fine-tune the structure of the sequences of the flights involved. Notably, from mid-January 2016 the difference between $Pc75$ and $Pmax$ shrinks whereas that between $Pmin$ and $Pc25$ expands, leading to a fall in the coefficient of variation that was not observed in December 2015. The equivalent fares in the control flights do not exhibit any such behavior and continue to remain at significantly lower levels. Overall, the analysis of the full booking period for the treated flights in 3N routes suggests that, although with a delay and to a smaller extent relative to the UK routes, the increase in NUM may have also played a role in shaping the sequences.

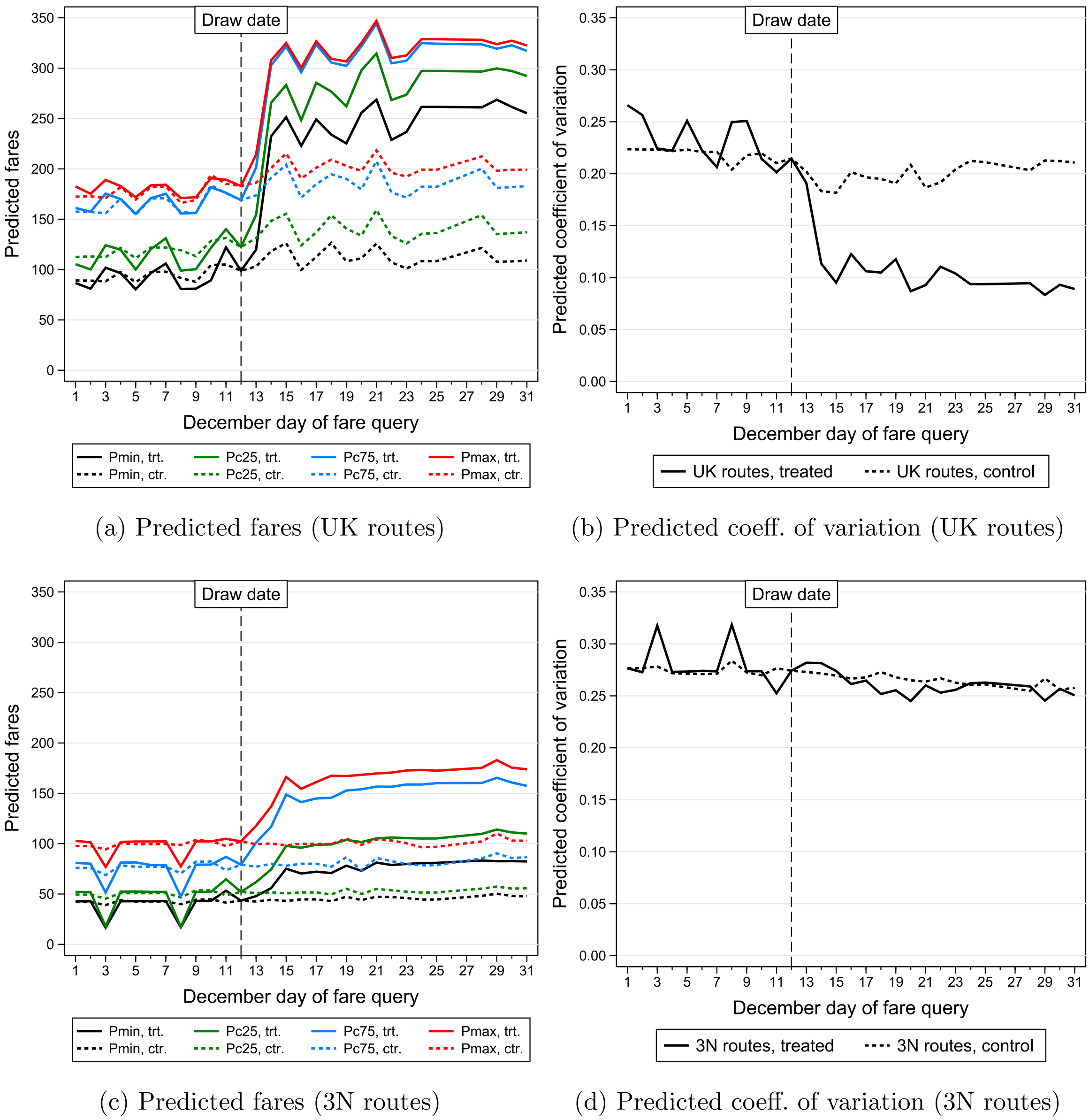
Relatedly, during January–March 2016 the tournament organizer, UEFA, had made arrangements that finalized the purchase of stadium tickets through a specialized website (Nicolini et al., 2023). The post-draw stability of the UK routes sequences and the peak reached by the 3N ones in March 2016 may reflect the dynamics of demand of flight services, which is complementary, and somewhat conditional, to gaining stadium entrance. The slight fall in subperiod B may be thus induced by the need to boost sales in those flights with a larger remaining capacity (Alderighi et al., 2015, 2016; Escobari, 2012; Williams, 2022).

Finally, as seats are sold over time, fewer fare classes remain available; indeed in subperiod C we observe that the four prices converge towards $Pmax$ in both treated and control flights (Alderighi et al., 2015). Relatedly, the coefficient of variation (shown in the right panels of Fig. 6) drops to its minimum value during the last month.

6.4. Robustness checks

As first robustness check, we replicate the entire econometric analysis using a different control group, the pre-tournament group. The results, reported in Appendix A.3, are qualitatively unchanged and confirm, on a larger sample, the conclusions of our analysis. Finally, we also run a placebo test which consists in changing the draw date and checking whether a similar hike in fares as the 'actual' draw date

[12] Note that such a distinction in subperiods applies to all four types of fares, confirming that any fare adjustment is not only timed to the lowest fare class ($Pmin$), but to the entire fare sequence.



(a) Predicted fares (UK routes) (b) Predicted coeff. of variation (UK routes)

(c) Predicted fares (3N routes) (d) Predicted coeff. of variation (3N routes)

Fig. 5. Predicted fares and coefficient of variation in December 2015 by subsamples.

is observed. As expected, the test shows that December 12th, 2015 is the only day to exhibit a large and statistically significant hike in fares. For further details on this placebo test see Appendix A.4.

7. Conclusion

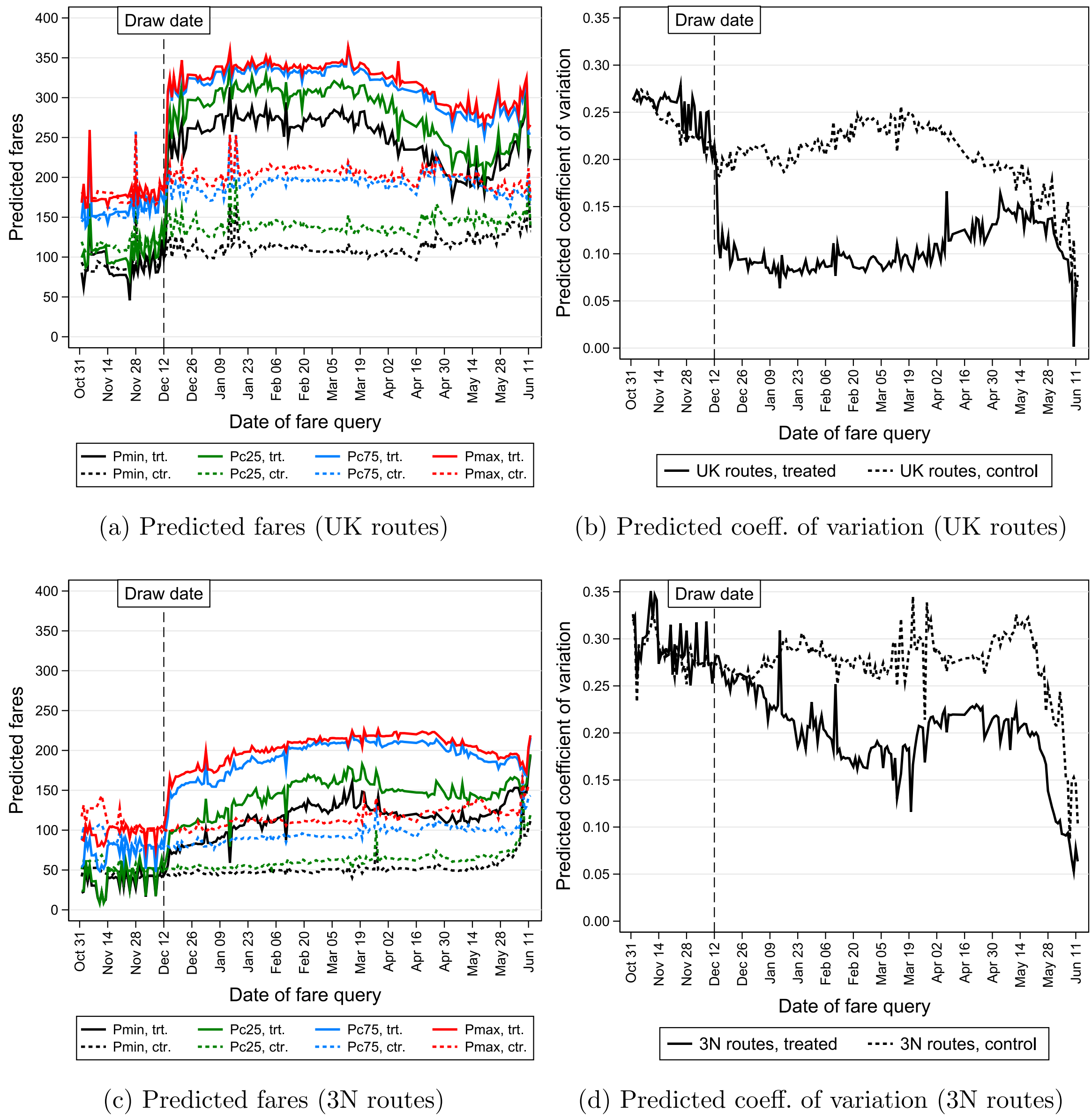
We investigated how a firm that sells multiple units of limited capacity items sequentially responds to a demand shock. We focused on the airline market, which represents a prominent example, but our analysis can apply to other sectors of the economy in which firms adopt revenue management techniques and set a sequence of prices to sell their products (e.g., hotel, car rental, train, long-distance bus, entertainment, sports industries).

In the theoretical model, the airline's maximization problem is to define, at each point in time, a sequence, i.e., a vector, of fares whose i^{th} element is paired to the i^{th} seat in the order of sale. Like in Alderighi et al. (2022), the optimal fare sequence is increasing in the order of sale. We show that a demand shock that affects only the distribution of the WTP only affects the level of the fares but not their dispersion; instead, an increase in the likelihood of a passenger showing up for purchase (NUM) is expected to lead to a flattening of the fare sequence, i.e., fewer seats are allocated to lower fare classes.[13]

The empirical analysis tests the predictions of the theoretical model using a natural experiment design that involves an exogenous positive shock in demand. We have employed the airline fares of a sample of flights serving France during the UEFA Euro 2016 soccer tournament. The flights affected by the shock were the ones that, after the draw revealed the identity of the teams playing in each French city, could be used by soccer supporters to reach the stadium and then return home.

The empirical evidence supports the main theoretical predictions and indicates that the fare sequences of these flights shifted up and became flatter, relative to unaffected flights. The first effect captures the increase in the value that consumers assign to the transport service, given the uniqueness of the sport event. The second effect points to an increase in the number of potential buyers that the airline factored

[13] The results would reverse in the case of a negative shock.



(a) Predicted fares (UK routes) (b) Predicted coeff. of variation (UK routes)

(c) Predicted fares (3N routes) (d) Predicted coeff. of variation (3N routes)

Fig. 6. Predicted fares and coefficient of variation over the booking period.

into their revised fare sequences. Most importantly, the evidence unequivocally supports the theoretical prediction that the fare sequence constitutes a primary revenue management tool used by easyJet, as the sequences were used in both treated and control flights, both before and after the shock. Piga and Alderighi (2024) discuss other strategic roles played by fare sequences, and how they relate to another assumption of the theoretical model, that is, the impossibility to adjust fares instantaneously due to both technological limitations and/or organizational frictions (Hortacsu et al., 2024). Indeed, we also find that the revision of fare sequences in treated flights was not immediately carried out by the airline.

These effects, however, are heterogeneous across routes and appear stronger on the flights linking France with United Kingdom (UK) than on the flights linking France with three of its neighboring countries (3N). After the draw, the price sequence of the UK flights responded relatively quickly, whereas the prices of the 3N flights were more sluggish to adjust and to show the same drop in price dispersion as the UK flights. Linking these findings to our theoretical model, the UK flights experience an increase in both WTP and NUM, with both effects, but the latter in particular, being weaker for the 3N flights. Because supporters from continental Europe could use alternative means of transport (car, train, long-distance bus) to reach the stadium, our findings suggest that fare sequences encompass a pricing tool that is flexible enough to manage flights with different degree of product substitutability.

We conclude by pointing out some possible limitations of the study and suggest reasons why they may not represent a serious concern. First, we show data based on only one airline, easyJet, raising doubts as to whether the use of fare sequences is common practice in the industry. Piga and Alderighi (2024) provide evidence that other such important low-cost players as Ryanair in Europe and Southwest in the USA also adopt a similar pricing approach. The evidence in Hortacsu et al. (2024), although not directly focused on fare sequences, also points to an equivalent mechanism being operational in traditional carriers. Second, the analysis does not control for the degree of route competition. Alderighi et al. (2022) address this specific point and find that fare sequences are used independently of the route's market structure. Hortacsu et al. (2024) also document that the pricing heuristic adopted by a large U.S. airline does not account for market characteristics. Finally, the empirical analysis focuses on the impact of the shock on prices but not on occupancy and realized load factors (Bilotkach et al., 2015; Escobari, 2012). Although obviously relevant, we left this aspect out and highlighted the role played by the fare sequences; its investigation is left for future research.

CRediT authorship contribution statement

Claudio A. Piga: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Data curation, Empirical Analysis, Conceptualization. **Alberto A. Gaggero:** Writing – original draft, Data curation, Empirical Analysis. **Marco Alderighi:** Theoretical model, Proof of Proposition 1, Simulations, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

A.1. Proof of Proposition 1

Part A. Starting from Eq. (2), we multiply both the left and the right-hand of the equation by $\alpha > 1$, obtaining:

$$\alpha V(t, M) = q\left(p_{t,m}\right)\left[\alpha p_{t,m} + \alpha V(t, M-1)\right] + \left(1 - q\left(p_{t,m}\right)\right)\alpha V(t-1, M), \tag{A.1}$$

After replacing $\hat{p} = \alpha p_{t,m}$ and $\hat{V} = \alpha V$, we have:

$$\hat{V}(t, M) = q(\hat{p}/\alpha)\left[\hat{p} + \hat{V}(t, M-1)\right] + (1 - q(\hat{p}/\alpha))\hat{V}(t-1, M), \tag{A.2}$$

Note that from Eq. (1), q can be written as:

$$q(\hat{p}/\alpha) = \frac{\varphi(1 - F(\hat{p}/\alpha))}{1 - \varphi F(\hat{p}/\alpha)} = \frac{\varphi\left(1 - \tilde{F}(\hat{p})\right)}{1 - \varphi\tilde{F}(\hat{p})} = \tilde{q}(\hat{p}) \in [0, 1], \tag{A.3}$$

Substituting Eq. (A.3) in Eq. (A.2), we obtain:

$$\hat{V}(t, M) = \tilde{q}(\hat{p})\left[\hat{p} + \hat{V}(t, M-1)\right] + (1 - \tilde{q}(\hat{p}))\hat{V}(t-1, M), \tag{A.4}$$

Thus, $\hat{p}$ in Eq. (A.4) is the solution for an analogous optimization problem for Eq. (2), where $\tilde{q}$ replaces q, say $\tilde{p}_{t,m}$. By construction, $\hat{p} = \alpha p_{t,m}$, and, therefore, optimal prices after the shock are: $\tilde{p}_{t,m} = \hat{p} = \alpha p_{t,m}$. Because all equilibrium prices are shifted up by α, the same occurs for the mean and the standard deviation. Consequently, the coefficient of variation, the ratio of these two measures, remains unchanged. This concludes the proof of Part A.

Part B. Recall that φ and $\tilde{\varphi}$ are, respectively, the parameter value without considering and after considering the positive shift in NUM, with $\tilde{\varphi} > \varphi$. In order to prove the result, we follow different steps.

Step 1: $\tilde{V}(t, m) \geq V(t, m)$. We first show that $\tilde{V}(t, m) \geq V(t, m)$ for any $t \in \{1, \ldots, T\}$ and $m \in \{1, \ldots, M\}$. Let $p_{t,m}$ be the optimal price before the shock. Choose $\hat{p}_{t,m}$ in such a way that $\tilde{q}(\hat{p}_{t,m}) = q(p_{t,m})$ for any t and m, i.e. $\hat{p}_{t,m} = \tilde{q}^{-1}(q(p_{t,m}))$. Because q and $\tilde{q}$ are decreasing, and $\tilde{q} > q$, it follows that $\hat{p}_{t,m} > p_{t,m}$ for any t and m.

Let $\hat{V}(t, m)$ be the value a firm receives by choosing the prices $\hat{p}$-s after the shift. By construction, with this choice, a firm faces the same pattern of sales that it obtains by charging the optimal prices p-s before the shift, but earns higher revenue for each unit sold. As a result, the value function satisfies $V(t, m) < \hat{V}(t, m) \leq \tilde{V}(t, m)$, where the last inequality arises because $\tilde{V}$ is the value function, i.e., the value a firm receives by choosing the optimal prices $\tilde{p}$-s.

Although $\hat{p}$-s are unlikely to be optimal prices after the shock, the previous discussion suggests the way in which prices should be modified after the shock, i.e., by shifting prices upward. In the next step, we prove that this conjecture is indeed true.

Step 2. $\tilde{p}_{1,1} \geq p_{1,1}$. When $t = 1$ and $m = 1$, Eq. (2) has the following first order condition:

$$\frac{q}{\dot{q}} + p = 0. \tag{A.5}$$

Let:

$$g := \frac{q}{\dot{q}} + p = -\frac{(1 - F)(1 - \varphi F)}{f(1 - \varphi)} + p. \tag{A.6}$$

Moreover, note that g and $(g - p)$ are decreasing in φ:

$$\frac{\partial g}{\partial \varphi} = \frac{\partial}{\partial \varphi}\left(\frac{q}{\dot{q}} + p\right) = \frac{\partial(g - p)}{\partial \varphi} = -\frac{(1 - F)(1 - \varphi F)}{f(1 - \varphi)} < 0.$$

From Eq. (A.5), since the first term is decreasing in φ, it follows that the optimal price p is increasing in φ, or $\tilde{p}_{1,1} \geq p_{1,1}$.

Step 3. $\tilde{p}_{t,1} \geq p_{t,1}$. For $t > 1$ and $m = 1$, the Bellman equation in (2) is simply:

$$\max_{p \in \Theta}\left\{q(p)p + (1 - q(p))V(t-1, 1)\right\}. \tag{A.7}$$

The first order condition is: $p + q/\dot{q} - V(t-1, 1) = 0$. As the second $(q/\dot{q})$ and third $(-V)$ terms are decreasing in φ (see, respectively Step 2 and Step 1), it follows that optimal prices are increasing in φ, i.e. $\tilde{p}_{t,1} \geq p_{t,1}$ for all t.

Step 4. $\tilde{p}_{1,m} \geq p_{1,m}$. Now, we consider the case where $t = 1$ and $m \geq 2$. The first order condition for any m is $p_m + q_m/\dot{q}_m + V(1, m-1) = 0$, $p_m = p_{1,m}$ and $q_m = q_{1,m} = q(p_{1,m})$. Note that, in this case the profit function can be written as:

$$\pi_m = q_m p_m + q_m q_{m-1} p_{m-1} + q_m q_{m-1} q_{m-2} p_{m-2} + \cdots + q_m q_{m-1} q_{m-2} \cdots q_1 p_1, \tag{A.8}$$

where π_m is the profit having m seats and $t = 1$ periods. The first order condition is:

$$\frac{q_m}{\dot{q}_m} + p_m + q_{m-1} p_{m-1} + q_m q_{m-1} q_{m-2} p_{m-2} + \cdots + q_m q_{m-1} q_{m-2} \cdots q_1 p_1 = 0, \tag{A.9}$$

where $\dot{q}_m = \partial q_m / \partial p_m$. After some substitutions, we obtain:

$$g_m = q_{m-1}(g_{m-1} - p_{m-1}), \tag{A.10}$$

where $g_m = q_m/\dot{q}_m + p_m$, $g_0 = p_0 = q_0 = 0$. We now use this equation to compute the optimal values of $p_{1,m}$ recursively, starting from 1 and ending in M.

Note that for $t = 1$ the optimal prices have a very simple graphical solution (see: Fig. A.1). The g curve has the following properties: it is increasing in p, $g(0) = -(f(0)(1 - \varphi))^{-1}$, $g(1) = \bar{\theta}$. The $q(g - p)$ curve is increasing, it equals $-\varphi(f(0)(1 - \varphi)^2)^{-1}$ in $p = 0$ and it is 0 in $p = \bar{\theta}$. To derive the optimal price solutions graphically, we start from the case in which $t = 1$ (see: Fig. A.1, Panel a).

Using Eq. (A.10), p_1 is given by the intersection of g with the horizontal axis, i.e., the solution of $g(p) = 0$. To obtain p_2, we move vertically down from p_1 to reach the curve $q(g - p)$ and then horizontally back to the g curve. Similarly, p_3 can be found graphically by moving vertically down from p_2 and then moving horizontally back to $q(q - p)$, and so on and so forth for the other prices until p_M. Following this line of reasoning, minimum equilibrium price $\underline{p}$ is when $g = q(g - p)$.

To show that prices are increasing in φ, we show that a marginal rise in φ increases p_1 and reduces the price difference $(p_{m-1} - p_m > 0)$ for any $m \geq 2$. The first claim implies that $\tilde{p}_1 \geq p_1$ while the second one implies that $\tilde{p}_m \geq p_m$). As g becomes steeper for any p and $g(\bar{\theta})$ does not change, it immediately follows that p_1 is increasing in φ (see also

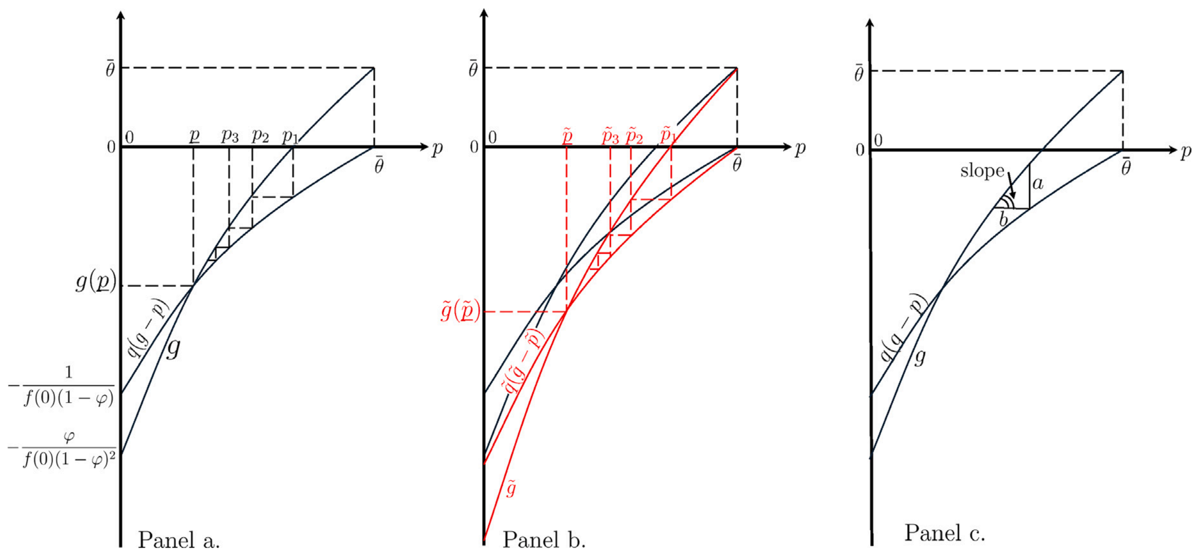


Fig. A.1. Optimal price sequence for $t = 1$ and $m \geq 1$.

Fig. A.1, Panel b).

Knowing that p_1 is increasing in φ, and noticing that the slope of g between p_{m-1} and p_m is simply the ratio of the difference between g_{m-1} and $q_{m-1}(g_{m-1} - p_{m-1})$ and the difference between p_m and p_{m-1} (see Fig. A.1, panel c, where the slope comes from the ratio between a and b). Consequently, $p_m - p_{m-1} = (g_{m-1} - q_{m-1}(g_{m-1} - p_{m-1}))/(\partial g/\partial p)$.

A sufficient condition for having (weakly) decreasing price differences in φ is that:

$$\frac{\partial}{\partial \varphi}\left[(g - q(g-p)) \cdot \left(\frac{\partial g}{\partial p}\right)^{-1}\right] \leq 0 \tag{A.11}$$

The condition is, for example, satisfied by the uniform distribution, indeed it is:

$$\frac{2p^2 - 3p + 1}{2(1 - \varphi p)^2} \leq 0, \tag{A.12}$$

which is satisfied for any $p \in [\underline{p}, \bar{p}] = [1/2, 1]$.

Step 5. $\tilde{p}_{t,m} \geq p_{t,m}$. Now, we consider the general case where $m \geq 2$ and $t \geq 1$. Note that, after generalizing the first order conditions in Eq. (A.9) we obtain the analogous of Eq. (A.10):

$$g_{t,m} = q_{t,m-1}(g_{t,m-1} - p_{t,m-1}) + [V(t-1,m) - V(t-1,m-1)], \tag{A.13}$$

This equation differs from the previous one by an extra-term $\Delta V = V(t-1,m) - V(t-1,m-1)$. From Step 1, we know that $V(t-1,m)$ and $V(t-1,m-1)$ are positive and increasing in φ. Moreover, the benefit obtained by a positive shift in φ increases the value of each seat, and, consequently, the impact is higher where the number of seat is higher, i.e., $\partial V(t-1,m)/\partial\varphi \geq \partial V(t-1,m-1)/\partial\varphi$. Using a similar argument employed in Step 4, we can compute the price difference that is now: $p_m - p_{m-1} = (g_{m-1} - q_{m-1}(g_{m-1} - p_{m-1} - \Delta V))/(\partial g/\partial p)$. Thus, the extra-term ΔV contributes to an additional reduction in price differences as φ increases, implying that $\tilde{p}_{t,m} \geq p_{t,m}$. This concludes the proof of part B.

Part C. We now prove that when φ and/or β are sufficiently large, $\tilde{p}_{t,1}/p_{t,1} < \tilde{p}_{t,m}/p_{t,m}$ and $\widetilde{CV}_{t,m} < CV_{t,m}$.

To do this, it is sufficient to show that when $\varphi \to 1$, $p_{1,m} \to \bar{\theta}$ and $p_{t,m} \to \bar{\theta}$ and, therefore, $CV_{t,m} \to 0$. Using Eq. (2) and taking the first derivative of the internal problem, we obtain:

$$\dot{q}(p)[p + V(t,m-1) - V(t-1,m)] + q(p) \tag{A.14}$$

Now, when $\varphi \to 1$, $q \to 1$, $\dot{q} \to 0$, and $[p + V(t,m-1) - V(t-1,m)] < \infty$, the first derivative is always positive. Thus, for any t and m, the optimal prices are $\tilde{p}_{t,1} = \tilde{p}_{t,m} = \bar{\theta}$ and $\widetilde{CV}_{t,m} = 0$. Moreover, we know that for any $\varphi < 1$, $t \leq T$, $m > n$, $p_{t,m} < p_{t,n}$ and $CV > 0$. Thus, we have proved the result for any $\varphi < 1$ and $\tilde{\varphi} = 1$. By continuity of the value function and optimal prices, for any t and m, there must exist a set of parameters φ and β such that for any $\tilde{\varphi} \in (\varphi, 1)$, we have: $\tilde{p}_{t,1}/p_{t,1} < \tilde{p}_{t,m}/p_{t,m}$ and $\widetilde{CV}_{t,m} < CV_{t,m}$. This concludes the proof of part C.

A.2. Parallel trends

In this subsection we use non-parametric tools to corroborate the evidence in favor of the parallel trends between the control and treatment groups during in the pre-draw period.

Fig. A.2 represents the median-spline of the mean by days to departure of four dependent variables used in the regression analysis: the lowest available fare ($Pmin$), the twenty-fifth percentile of the fare sequence ($Pc25$), the seventy-fifth percentile of the fare sequence ($Pc75$), and the highest observable fare ($Pmax$). The average is computed within each date of query and for different groups of flights.

As the figure shows, prior to the draw the pattern of the treated flights (solid curves) and the corresponding control flights (dashed curve) tend to be similar and, in some instances, even overlap. This behavior is observed in all the four panels, i.e., for all the four fare variables used in the regressions, and may support the idea that in absence of the shock the fares of the treated flights would have probably behaved in the same way as the fares of the control flights. Under this argument we claim that the difference between the treatment and the control group that we observe in the post-draw period is due to the draw, or, using a more general term, to the demand shock (see Fig. A.2).

A.3. Pre-tournament flights as control group

Figs. A.3, A.4, and A.5 are obtained replicating the entire econometric analysis of the paper using the pre-tournament flights as control group. Therefore, they represent the companions of Figs. 4, 5, and 6, respectively.

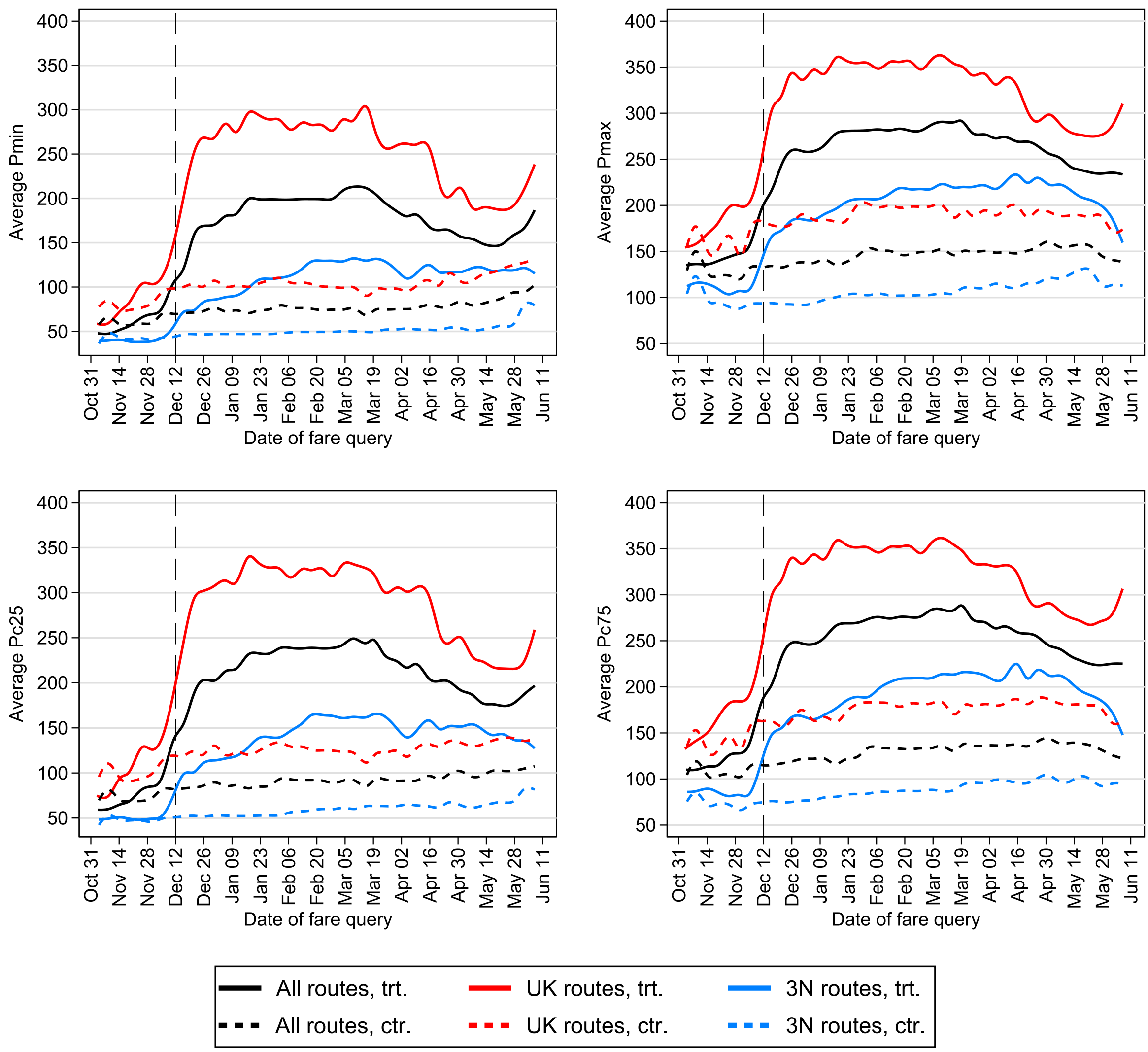


Fig. A.2. Median-spline of the mean fare over the booking period.

Noticeably, Figs. A.3, A.4, and A.5 lead to the same conclusions shown by the figures in the main body of this article thereby confirming our findings using an alternative control group.

A.4. Placebo test

To check the robustness of our findings further, we conduct the following placebo test. We set a hypothetical draw date which takes the place of the real draw date of December 12th, 2015 and then estimate the following equation:

$$Y_{it} = \beta_0 + \beta_1 Post_t + \beta_2 Treated_i + \beta_3 (Post_t \cdot Treated_i) + \varepsilon_{it} \qquad (A.15)$$

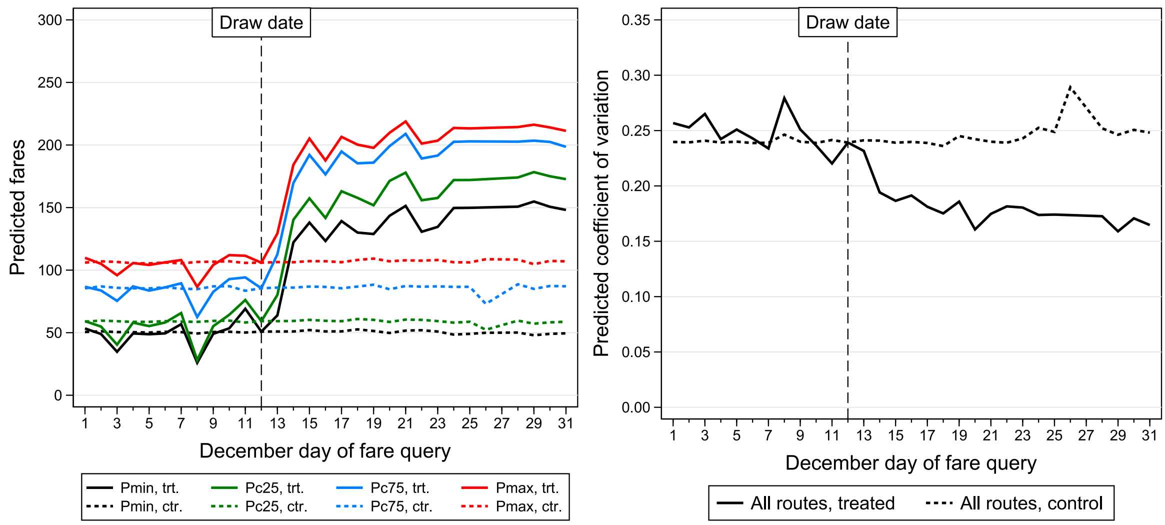
on an even sub-sample which includes up to 30 days before and 30 days after the hypothetical draw date denoted by the dummy variable $Post$. We use $Pmin$ as dependent variable. We start by selecting February 1th, 2016 as the first hypothetical draw date and then repeat the process shifting the hypothetical draw date by one day onward until May 1th, 2016. We run 82 regressions in total. Fig. A.6 displays the estimated β_3 coefficient of Eq. (A.15) with its 95% confidence interval.

For hypothetical draw dates prior to mid March we observe instances of positive β_3; however the coefficient is statistically significant from zero in few cases and, above all, its magnitude is no more than 11, while the same estimation using the real draw date yields a statistically significant β_3 coefficient equal to almost 74. When the hypothetical draw date is set from mid March onward, the β_3 coefficient is statistically significant but negative, which is inconsistent with a positive demand shock for treated flights.

Both findings suggest that all the fares of treated flights reacted to a positive demand shock induced by the draw on December 12th, 2015.

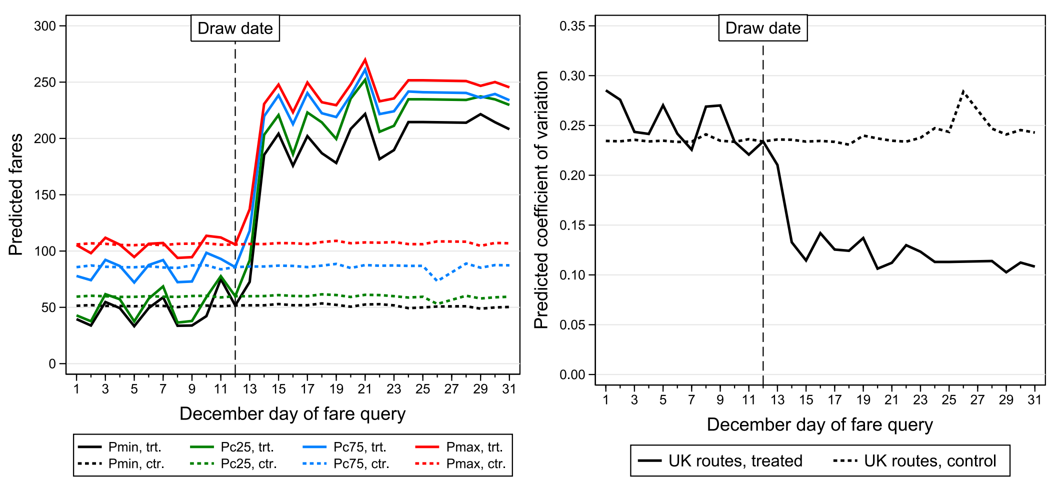
Data availability

Data will be made available on request.

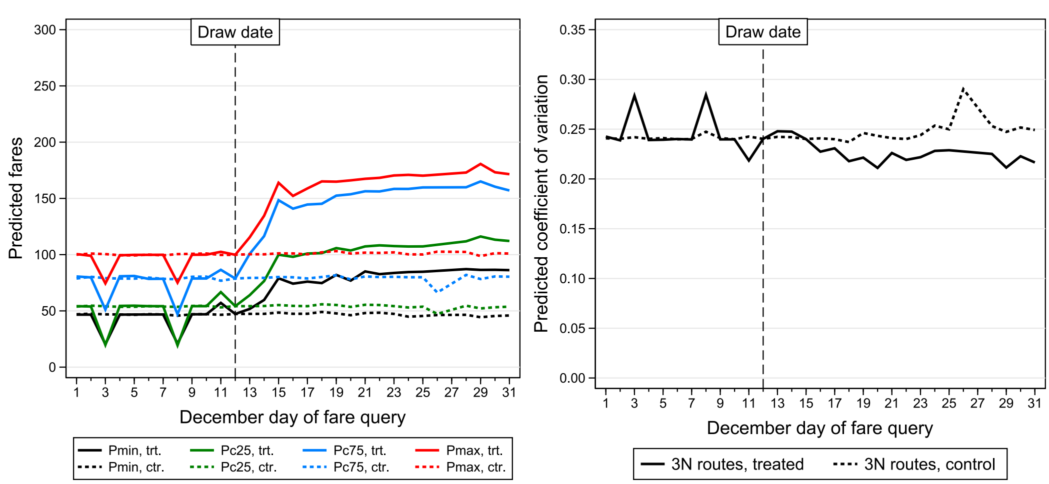


(a) Predicted fares (b) Predicted coefficient of variation

Fig. A.3. Predicted fares and coefficient of variation in December 2015 with pre-tournament control group.

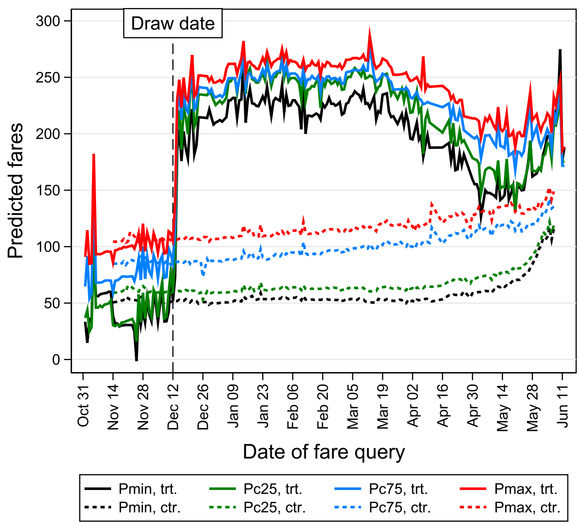


(a) Predicted fares (UK routes) (b) Predicted coeff. of variation (UK routes)

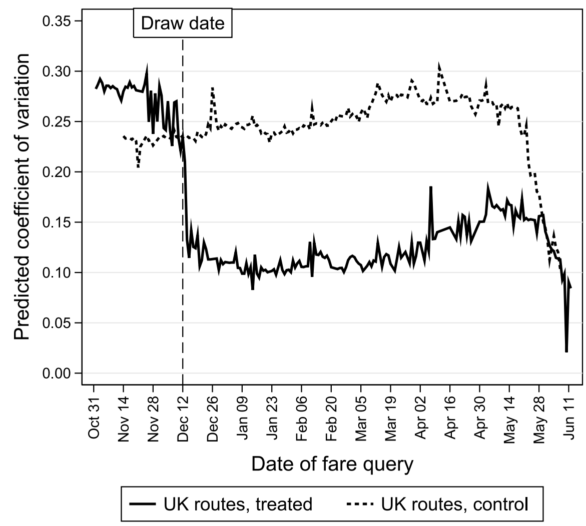


(c) Predicted fares (3N routes) (d) Predicted coeff. of variation (3N routes)

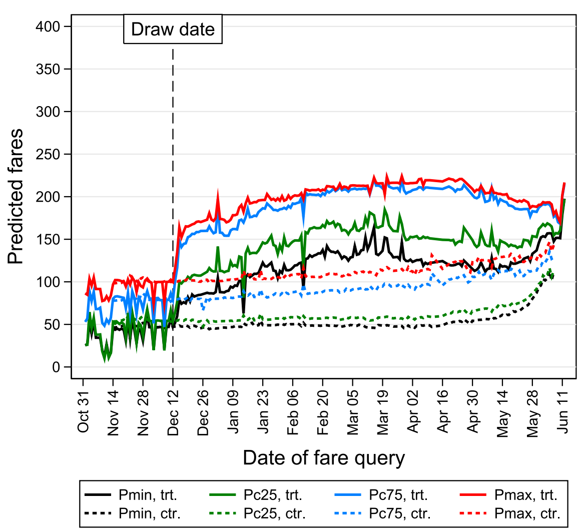
Fig. A.4. Predicted fares and coefficient of variation in December 2015 by subsamples with pre-tournament control group.



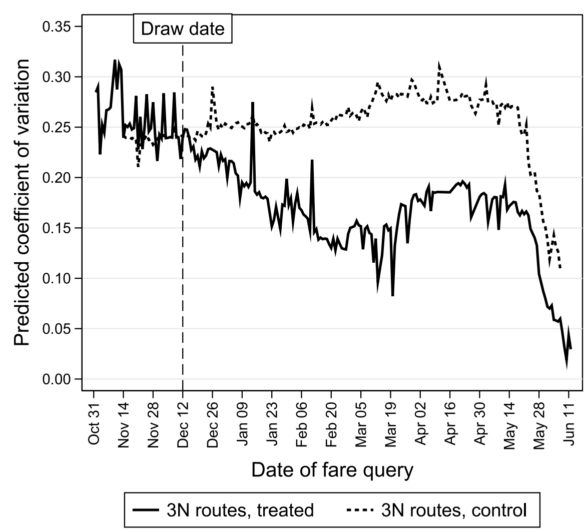
(a) Predicted fares (UK routes)



(b) Predicted coeff. of variation (UK routes)



(c) Predicted fares (3N routes)



(d) Predicted coeff. of variation (3N routes)

Fig. A.5. Predicted fares and coefficient of variation over the booking period with pre-tournament control group.

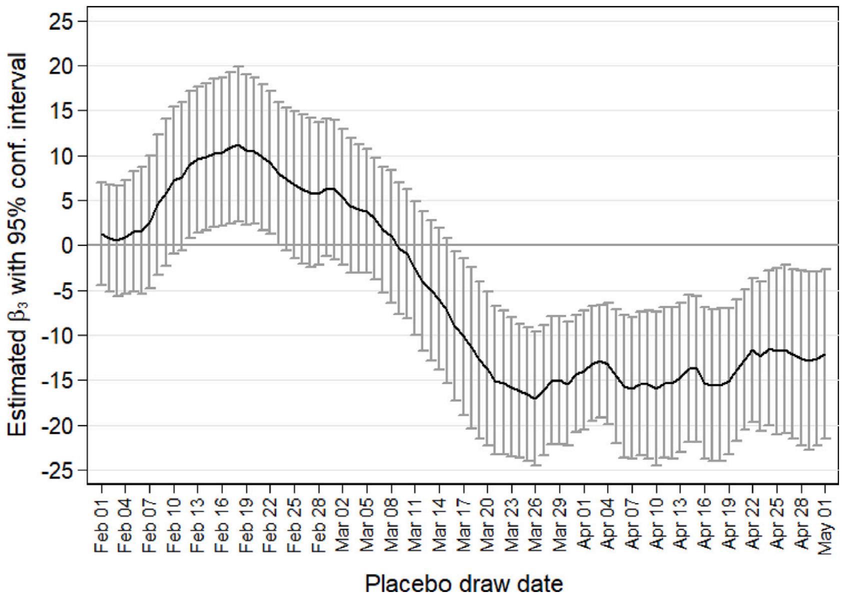


Fig. A.6. Placebo test: $\hat{\beta}_3$ from Eq. (A.15) with different draw dates.

References

Alderighi, M., Gaggero, A.A., Piga, C.A., 2022. Hidden prices with fixed inventory: evidence from the airline industry. Transp. Res. B 157, 42–61.

Alderighi, M., Nicolini, M., Piga, C.A., 2015. Combined effects of load factors and booking time on fares: insights from the yield management of a low-cost airline. Rev. Econ. Stat. 97, 900–915.

Alderighi, M., Nicolini, M., Piga, C.A., 2016. Targeting leisure and business passengers with unsegmented pricing. Tour. Manag. 50, 502–515.

Angeletos, G.-M., Lian, C., 2022. Confidence and the propagation of demand shocks. Rev. Econ. Stud. 89 (3), 1085–1119.

Aryal, G., Murry, C., Williams, J.W., 2023. Price discrimination in international airline markets. Rev. Econ. Stud..

Bai, Y., Ríos-Rull, J.-V., 2015. Demand shocks and open economy puzzles. Amer. Econ. Rev. 105 (5), 644–649.

Baker, J.B., 1989. Identifying cartel policing under uncertainty: the US steel industry, 1933–1939. J. Law Econ. 32 (2, Part 2), S47–S76.

Balvers, R.J., Cosimano, T.F., 1990. Actively learning about demand and the dynamics of price adjustment. Econ. J. 100 (402), 882–898.

Belobaba, P.P., 2009. Fundamentals of pricing and revenue management. In: Belobaba, P., Odoni, A., Barnhart, C. (Eds.), The Global Airline Industry. Wiley & Sons, Chichester, UK, pp. 73–112.

Berman, N., Rebeyrol, V., Vicard, V., 2019. Demand learning and firm dynamics: evidence from exporters. Rev. Econ. Stat. 101 (1), 91–106.

Bilotkach, V., Gaggero, A.A., Piga, C.A., 2015. Airline pricing under different market conditions: evidence from European low-cost carriers. Tour. Manag. 47, 152–163.

Bilotkach, V., Gorodnichenko, Y., Talavera, O., 2012. Sensitivity of prices to demand shocks: A natural experiment in the San Francisco bay area. Transp. Res. Part A: Policy Pr. 46 (7), 1137–1151.

Borenstein, S., Rose, N.L., 1994. Competition and price dispersion in the U.S. airline industry. J. Polit. Econ. 102, 653–683.

Copeland, A., Hall, G., 2011. The response of prices, sales, and output to temporary changes in demand. J. Appl. Econometrics 26 (2), 232–269.

Dana, J.D., 1999. Equilibrium price dispersion under demand uncertainty: The roles of costly capacity and market structure. Rand J. Econ. 30 (4), 632–660.

Escobari, D., 2012. Dynamic pricing, advance sales, and aggregate demand learning in airlines. J. Ind. Econ. 60 (4), 697–724.

Gaggero, A.A., Luttmann, A., 2022. How does COVID-19 affect intertemporal price dispersion? Evidence from the airline industry. In: Mpra Paper. University Library of Munich, Germany.

Gaggero, A.A., Piga, C.A., 2011. Airline market power and intertemporal price dispersion. J. Ind. Econ. 59 (4), 552–577.

Gagnon, E., López-Salido, D., 2020. Small price responses to large demand shocks. J. Eur. Econom. Assoc. 18 (2), 792–828.

Gerardi, K., Shapiro, A., 2009. Does competition reduce price dispersion? New evidence from the airline industry. J. Polit. Econ. 117, 1–37.

Hall, T.E., Fields, T.W., 1987. Anticipated nominal demand shocks and the speed of aggregate price adjustment. Rev. Econ. Stat. 140–144.

Hortacsu, A., Natan, O.R., Parsley, H., Schwieg, T., Williams, K.R., 2024. Organizational structure and pricing: Evidence from a large U.S. airline. Q. J. Econ. 139 (2), 1149–1199.

Kwapil, C., Scharler, J., Baumgartner, J., 2010. How are prices adjusted in response to shocks? Survey evidence from Austrian firms. Manag. Decis. Econ. 31 (2/3), 151–160.

Lacetera, N., Piga, C.A., Zirulia, L., 2024. Sticky price for declining risk? Business strategies with "behavioral" customers in the hotel industry. J. Econ. Manag. Strat. Early View.

Lim, N., Kim, S., Agarwal, R., 2022. Weathering a demand shock: the impact of prior vertical scope on post-shock firm response. Strat. Manag. J..

Menezes, F.M., Quiggin, J., 2022. Market power amplifies the price effects of demand shocks. Econom. Lett. 221, 110908.

Nicolini, M., Piga, C.A., Pozzi, A., 2023. From uniform to bespoke prices: Hotel pricing during EURO 2016. Quant. Mark. Econ. 21, 333–355.

Orlov, E., 2011. How does the internet influence price dispersion? Evidence from the airline industry. J. Ind. Econ. 59 (1), 21–37.

Phillips, R.L., 2005. Pricing and Revenue Optimization. Stanford University Press, Stanford, CA.

Piga, C.A., Alderighi, M., 2024. Capacity, static and dynamic pricing: theory and evidence. Working paper 5029318, SSRN.

Siegert, C., Ulbricht, R., 2020. Dynamic oligopoly pricing: Evidence from the airline industry. Int. J. Ind. Organ. 71.

Tokar, T., Aloysius, J., Williams, B., Waller, M., 2014. Bracing for demand shocks: an experimental investigation. J. Oper. Manage. 32 (4), 205–216.

Wei, F., Chen, J., Zhang, L., 2017. Demand shocks, airline pricing, and high-speed rail substitution: evidence from the Chinese Market. J. Transp. Econ. Policy 51 (4), 266–289.

Williams, K.R., 2022. The welfare effects of dynamic pricing: evidence from airline markets. Econometrica 90 (2), 831–858.