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AIRLINE PRICING UNDER DIFFERENT MARKET CONDITIONS: EVIDENCE FROM EUROPEAN LOW-COST CARRIERS

Airline Pricing under Different Market Conditions: evidence from European Low-Cost Carriers*

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Abstract

Traditional theories of airline pricing maintain that fares monotonically increase as fewer seats remain available on a flight. A fortiori, this implies a monotonically increasing temporal profile of fares. In this paper, we exploit the presence of drops in offered fares over time as an indicator of an active yield management intervention by two main European Low-Cost Carriers observed daily during the period June 2002 - June 2003. Our results indicate that yield management is effective in raising a flight's load factor. Furthermore, yield management interventions are more intense, and generate a stronger impact, on more competitive routes: one possible interpretation is that a reduction in competitive pressure allows the carriers to adopt a more standardized approach to pricing. Similarly, we find that yield management interventions are more effective in raising the load factor on routes where the customer mix is more heterogenous (i.e., it includes passengers traveling for leisure, business and for family matters). On markets with homogeneous customer base, no robust yield management effect was observed.

JEL Classification: D22, L11, L93.

Keywords: Easyjet, Intertemporal Pricing, Panel Data, Ryanair, Yield Management.

1 Introduction

Pricing in the airline industry is highly complex. One result of this complexity is substantial price dispersion: passengers end up paying vastly different prices for an otherwise identical service. Borenstein and Rose (1994) ascribe dispersion in airline fares to

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two main sources: peak-load pricing (both systematic and stochastic), and price discrimination.[1] In practical terms, the airlines operationalize the latter by introducing a number of segmenting devices known as "fences" (e.g., the Saturday night stayover and the advance-purchase requirements). Because fares have to be set before demand is realized, airlines deal with peak-load pricing by practicing "yield management" (hereinafter, YM), which refers to pricing perishable fixed capacity under uncertain demand to maximize load factor and revenue. As Dana (1999a) illustrates in a model where market segmentation and price discrimination are not technically feasible, systematic peak-load pricing can be effectively tackled by YM techniques that require reliable forecasts on the number of possible demand states and their probability of occurring. However, in the event the forecasts turn out to be particularly imprecise and/or if unexpected contingencies arise, the need to deal with stochastic peak-load pricing may induce airlines to revise the pricing schedule they devised under systematic peak-load conditions. This is particularly important when the actual demand is much lower than expected so that, in the absence of any rectifying intervention that shifts at least some fares downward, the aircraft would be likely to depart with many empty seats.[2]

In this paper, we investigate whether YM interventions in the form of fare reductions, which we identify as persistent "price drops" over time, are effective in raising a flight's realized load factor. In particular, we focus on whether an airline's YM efforts have a stronger impact in market situations where the need to revise a previously set pricing schedule is more likely; i.e., in competitive markets, where revision may be induced by an unpredicted change in competitors' pricing behavior; and in markets with a more heterogeneous demand, so that fares need to adjust to a different mix of travelers's types, whose realization over time may be highly idiosyncratic. To our knowledge, this paper represents the first study relating offered price profile in the airline industry as the departure day nears to the flight's final number of passengers. In fact, it is difficult to obtain official statistics on single flights' load factors.

A typical problem that arises in empirical studies of airline pricing is that YM

[1] Under systematic peak-load pricing, the high- or low-demand periods can be predicted with sufficiently accurate precision, while stochastic peak-load pricing entails the management of demand conditions that could not be determined a priori.

[2] Arguably, the financial incentive to revise a flight's pricing schedule downward is larger than in the case where demand turns out to be higher than expected. Firstly, an alternative to lowering fares could be canceling the flight, a tactic that, in Europe, incurs penalties if excessively practiced. Secondly, the perishability of seats implies that any paid seats is obviously preferable to an empty seat. Thirdly, states of high demand are automatically managed within systematic peak-load pricing schedules by assigning very high fares to the last batches of seats, i.e., those that are generally least likely to be sold.

induced by demand uncertainty is intertwined with price discrimination strategies. Indeed, airlines typically offer contracts, which include price and refundability clauses. Usually, cheaper tickets are not refundable, and travelers must pay a premium if they would like to retain the possibility of adjusting their travel plans after buying the ticket. This makes differently priced tickets not directly comparable. Additionally, the airlines often price the same seat differently, depending on whether the customer travels one-way or round-trip. In this paper, we make use of a unique dataset of price quotes by the two leading European Low-Cost Carriers (LCCs). The advantage of our dataset is that all the tickets are offered as strictly non-refundable contracts, irrespective of the price, and the airlines do not practice any discrimination between one-way and round-trip customers. Additionally, our data allows us to abstract from pricing-in-network considerations, as the carriers involved only sell tickets for point-to-point services. Specifically, we observe both the evolution of price quotes for a number of flights as the departure date nears, and the realized load factors of those flights; hence we can study how realized load factors are influenced by YM interventions represented by unexpected price reductions observed at various time intervals prior to a flight's departure.

The hypothesis that price drops are designed to increase a flight's realized load factor finds support in our data, within an econometric flight-level fixed effects model that accounts for the potential endogeneity of the price drops variable. The effect of YM is particularly pronounced on competitive routes, and on the routes where customers are heterogeneous (i.e., represent a mix of business and leisure travelers).

This study offers the first empirical analysis of yield management in economics literature. Our results indicate that active YM interventions by the airlines are effective in raising the flight load factor. We must however note two caveats here. First, intertemporal price discrimination is not an alternative hypothesis to our contention, and our finding that YM is practiced effectively does not mean that the airlines do not price discriminate. It is simply that, according to the available information on how airline set their fares, the temporal price discrimination approach is largely a fixed effect, i.e., a similar template is applied across daily flights operated on the same route sharing the same time of departure. Furthermore, the use of relevant instruments is also designed to purge the yield management variable of possible other time-varying flight-specific effects. Second, we do not claim to have conducted a completed analysis of the full range of yield management practices. Indeed, we only focus on one particular manifestation, i.e., sustained price drops induced by stochastic peak-load pricing considerations, but we also control for other more traditional forms of yield management such as those discussed in Dana (1999a, 1999b), where the emphasis lies on how fares should be adjusted to reflect systematic peak-load pricing considerations. Since we only deal with final realized load factors, we cannot study whether the management of peak-load pricing varies with market conditions; addressing this issue will probably require more detailed data on how fares change as a plane fills up.

The rest of the paper is organized as follows. The next section discusses relevant literature. This is followed by discussion of our approach to measure yield management. Sections 4, 5, and 6 discuss data, empirical strategy, and results, respectively. Section 7 concludes. Some secondary results are in the Appendix.

2 Literature Review

The theoretical literature on airline pricing has focussed on YM techniques aimed at implementing systematic peak-load pricing and advance-purchase discounts at the single flight level. As Dana (1999b) illustrates in a model with demand uncertainty and perishable assets, systematic peak-load pricing can be effectively managed by dividing the total of the aircraft's seats into groups or "buckets" (McGill and Van Ryzin, 1999), whose number and size depend on the number of possible demand states and their probability of occurring; and by assigning to each bucket a fare whose level is inversely related with the probability that a seat in that group is sold.[3] A similar mechanism is proposed in Dana (1999a) to shift demand from peak to off-peak flights when airlines do not know ex-ante for which flight the peak will be realized: because in equilibrium the airline restricts the size of the low-priced buckets, some consumers choose to fly at their least preferred time.

Advance-purchase discounts (APD, hereafter) provide a simple way to screen consumers by their demand uncertainty. Gale and Holmes (1993) argue that in a monopoly with capacity constraints and perfectly predictable demand, APD are used to divert demand from peak periods to off-peak periods in order to maximize profits. By doing so, the airlines price discriminate across customers on the basis of their price elasticity and time valuation. Similarly, when the demand is uncertain ADP help to improve profitability by spreading customers evenly across flights before the peak period is

[3]Furthermore, Dana (1999b) provides theoretical support to some of the previously mentioned empirical studies where price dispersion is found to be larger in competitive markets.

known (Gale and Holmes, 1992). Finally, Dana (1998) demonstrates that in competitive markets where prices are set before the demand is known, the application of a "low-before-high-fares" strategy is driven by the fact that consumers with more certain demand are more likely to buy in advance. More recently, Möller and Watanabe (2010) have compared APD with clearance sales, and illustrated how the former are more appropriate when a consumer faces no or little risk of being rationed.

To sum up, the highly unanimous conclusion from the theoretical airline pricing literature is a strong support for fares being monotonically increasing over time. Indeed, although the results in Dana (1999a and 1999b) are obtained by ruling out any form of intertemporal price discrimination, they can be seen as observationally equivalent to it, since prices increase monotonically as buckets are filled, and hence a fortiori they have to increase over time. This property is largely due to the assumption that demand is allocated by rationing (as in Prescott (1975) and Eden (1990)) and not market clearing; alternatively put, under this assumption pricing decisions are set once and for all, i.e., the airlines are irrevocably committed to follow them. The frequent observation in our dataset of price drops is thus in stark contrast with the monotonic property. A possible way to reconcile the theoretical literature on airline pricing with empirical observation follows from the consideration that the airlines may be adopting the two-stage process indicated in European Commission (2007). According to this process, a pricing profile, which defines the buckets' properties as well as any temporal variation, is initially set for each flight. Subsequently, a yield manager may choose to intervene by reducing the fares in order to try to clear the market. This latter aspect is largely consistent with our definition of price drops as YM interventions.

In the extant literature, as the previous discussion highlights, YM often takes a multi-faceted connotation. Dana (1999b) indicates that YM can be used as a tool to implement intertemporal, second and third-degree price discrimination; but it also implements peak-load pricing and an inventory control system for coping with uncertain demand for a perishable asset. Generally, as the 'price discrimination like' outcomes appear where the firms do not have market power, disentangling the motives behind the observed pricing behavior by the airlines, and attributing them to a specific type of YM becomes an intriguing topic for research that is often hindered by limitations in the data availability.

Although the theoretical literature on yield management is rather extensive and well developed, its empirical counterpart is scarce, recent, and does not offer any unambiguous results. This is mostly due to the scarcity of appropriate data, and the complexity of the data generating processes. Two recent studies attempt to test yield management theories of pricing in the airline industry. The studies use different datasets, and arrive at fundamentally different results. Escobari and Gan (2007) collect fare quotes for a number of flights, tracing evolution of offered prices as the departure day nears. This approach is similar to what we do in our study. The authors also derive a proxy for the load factor at each date of price data collection to evaluate the probability that the flight will be sold out. The main finding is that lower selling probability yields higher price quote, as predicted by the peak-load, inventory control models. In contrast, Puller et al. (2009) argue that the observed price pattern is consistent with price discrimination rather than YM. Both these studies, however, use data generated by a more complex process than the one described by any of the models in the literature. Both papers deal with pricing of non-stop one-way flights operated by the network airlines, without taking into consideration the well-known discrimination between one-way and round-trip passengers. Also, seats on the same aircraft are occupied by origin-destination and transit passengers, and presence of transit passengers can affect pricing of the origin-destination tickets. Further, while Puller et al. (2009) are able to control for various ticket restrictions, they had to resort to estimating the flight-level load factors from their data and another dataset which provides more aggregate information. Escobari and Gan (2007), on the other hand, do not give adequate consideration to the possible differences in restrictions attached to the fare quotes in their sample.

Also related to our study is the literature on price dispersion in industries characterized by costly capacity, asset perishability, and demand uncertainty. Studies of price dispersion in the airline industry include Borenstein and Rose (1994), Gerardi and Shapiro (2009), Gaggero and Piga (2011), Stavins (2001), Hayes and Ross (1998), Hernandez and Wiggins (2009). Of these, Hayes and Ross (1998) and Stavins (2001) suggest the link between the strategies attributed to yield management and observed price dispersion. However, neither of the two studies had a rich enough dataset to offer a more comprehensive analysis of the issue.

Our dataset, although it lacks information on the flight occupancy at the moment fares were retrieved, presents the advantage that it is generated from a setting which is very close to the one actually modeled by theoretical studies. Specifically, carriers in our sample focus exclusively on point-to-point travel; they do not discriminate between one-way and round-trip ticket purchasers; and neither offer refundable tickets, nor employ other ‘fences’. Importantly, we observe flight-level realized load factors. Therefore, our empirical strategy differs from the one employed by Escobari and Gan (2007), and Puller et al. (2009) in that we focus on the impact of evolution of the price quotes prior to the departure date on the realized load factor. In this way, we are able to study whether and to what extent YM, defined as a revision to a pre-determined pricing profile, is practiced by the carriers and how effective it is in raising a flight’s load factor.

3 Methodology

Our empirical strategy involves using the flight’s realized load factor as the dependent variable. At the most general level, load factor is the outcome of the level of demand, market competition, and the airline’s strategy. When setting its price, the airline is driven by what it knows about the potential passengers’ willingness to pay, as well as by the realized demand. As far as the passengers’ willingness to pay is concerned, we assume that the airline takes into account the correlation between the customers’ willingness to pay and how early a booking is made. That is, more price sensitive leisure travelers, whose demand uncertainty is solved earlier, book their flight before less price sensitive business travelers. The airline can take advantage of this pattern, practicing intertemporal price discrimination.

Therefore, prima facie, our proposed measure of YM intervention based on price drops appears to be observationally equivalent to intertemporal price discrimination. However, we can separate and gauge the net impact of YM interventions by exploiting a number of aspects that characterize the airlines’ pricing behavior. Specifically, the temporal profile of fares induced by discriminatory purposes tends to be flight-specific and is generally repeated over time. By definition, price drops induced by YM interventions are idiosyncratic, and therefore flights with such interventions will exhibit a different temporal profile. Furthermore, given the large evidence of fares increasing sharply in the last ten days from departure, we argue that sustained price drops as the departure date nears are consistent with yield management, but not with intertemporal price discrimination.

We essentially suppose that the airline practicing intertemporal price discrimination sets its offered prices according to some profile, which is determined based on some averaged information about demand. Then, if demand realization profile is different from that expected 'average', the airline uses yield management to adjust prices. Specifically, when seats are not selling as fast as the profile has predicted, the carrier either postpones the planned price increase, or lowers the price. However, because the last buckets of seats are already priced so as to reflect high peaks in demand, it is unlikely that when customers arrive at a higher rate than anticipated, a carrier will modify a preset price profile, which already includes automatic increases. Dana (1999a) indeed suggested that booking limits are relaxed more frequently than they are tightened, meaning that yield managers are more likely to react when demand is below projections than when seats are sold faster than expected. Overall, this approach is largely consistent with the description of the YM systems operated by Ryanair and Aer Lingus made by the European Commission in its investigation of the merger proposal that was blocked in 2007.[4] The Commission emphasizes how these carriers adopt a set of standard "templates" (i.e., a combination of buckets' prices and sizes), whose choice depends on a flight's and its route's characteristics. There are expected to remain largely invariant unless, as discussed above, realized demand diverges significantly from its forecast.

The issue is then to identify the above-mentioned deviations from the average in the data. This is not a straightforward task, since it is not clear which - if any - offered price trajectory in our dataset represents the average intertemporal price discrimination pattern. In light of the above suggestion that yield managers are likely to respond to demand realization when it is below its projection, then the only deviation from the average price trajectory, which we can clearly see in the data, involves cases of *drops in the offered prices* over consecutive periods. Price drops will be the focus of our analysis, aimed at identifying and quantifying the effects of YM on realized load factors.

Before we continue with the discussion of our dataset, we need to remind the reader that we will not be able to offer the comprehensive judgement of the effectiveness of YM in our study. Our investigation will, however, inform us about and quantify the effects of one particular manifestation of YM. Also, while the goal of YM is to both increase the load factors and maximize revenue, our paper focuses on the former objective, for lack of the detailed revenue data.

[4]See Commission Decision (2007) on Case No COMP/M.4439 – Ryanair/Aer Lingus, pp. 108-109

4 Data

Our dataset consists of three parts. First, we use information on offered prices (fare quotes in British Sterling £) of the two leading European low cost carriers (LCCs): Ryanair and Easyjet.[5] The price quotes have been collected on 130 routes [6] both within the United Kingdom, and between the United Kingdom and a number of European countries.[7] We have used an "electronic spider" to collect fare quotes by connecting directly to the web sites of the two leading LCCs daily from June 2002 until June 2003. Overall, we have identified 843 unique flight codes, served by the two carriers. Fare quotes were collected 1, 4, 7, 10, 14, 21, 28, 35, 42, 49, 56, 63 and 70 days prior to the departure day for each flight code. Each of these is denoted as a "booking day". The highest frequency of late booking days is meant to allow possible APD effects, an issue that appears to be particularly relevant for both these airlines, as illustrated in Dobson and Piga (2011). Overall, we have collected thirteen fare quotes for each flight.

Table 1 reports descriptive statistics (average fare quotes and corresponding standard deviations) depending on how far in advance the fare quotes have been collected. The numbers are reported both for the entire sample, and for sub-samples of competitive and not competitive routes; see Section 6.2 below for a detailed discussion of these sub-samples.

We can infer from Table 1 that price quotes depict a generally increasing trend as the flight date nears; and that prices tend to be higher on routes that are less competitive. Both results hold also when we analyze each carrier separately. Furthermore, our dataset includes a potentially non-trivial number of cases of decreases in offered price over time. Specifically, the average price quote 21 days prior to departure is lower than the same a week before (28 days prior to the flight date). Although this is mostly driven by data from EasyJet, a similar fall over consecutive booking days is observed for Ryanair between 63 and 56 days from departure.

The other two parts of the dataset are derived from official statistics. The second data source we use is the information on realized flight load factors. Specifically, the

[5]Ryanair and Easyjet are two largest low-cost carriers in Europe. Ryanair is based in Ireland, and Easyjet is headquartered in the United Kingdom. However, both carriers perform services throughout Europe. In 2010, Ryanair carried over 70 million passengers; Easyjet's total for the same year was over 45 million. By this parameter, the carriers are both among the top five European airlines.

[6]Those routes are not the universe of markets served by Ryanair and Easyjet, however they are randomly selected to be good representatives of the entire route-population.

[7]Austria, Belgium, Check Republic, France, Germany, Greece, Italy, Ireland, Netherlands, Norway, Spain, Sweden, and Switzerland

Table 1: Average Price across Booking Days

Booking Days	Full sample All Routes	Easyjet Low Comp.	Easyjet High Comp.	Ryanair Low Comp.	Ryanair High Comp.
1	82.6	79.4	71.8	97.7	75.9
	(43.86)	(39.38)	(35.11)	(45.13)	(48.3)
4	62.8	62.9	56.6	74.4	53.1
	(37.21)	(32.08)	(30.53)	(41.63)	(36.63)
7	49.9	54.9	46.3	56.4	40.4
	(35.2)	(30.17)	(26.55)	(40.84)	(35.78)
10	46.3	50.0	42.7	52.6	38.4
	(34.73)	(28.79)	(27.49)	(39.94)	(36.07)
14	41.6	51.2	40.6	44.5	31.3
	(32.69)	(31.73)	(28.66)	(35.46)	(30.49)
21	38.2	50.1	38.4	39.4	27.3
	(31.37)	(32.5)	(29.07)	(32.57)	(27.39)
28	39.0	56.4	42.0	37.1	25.1
	(35.04)	(39.62)	(34.74)	(33.52)	(26.64)
35	34.5	52.9	38.5	31.2	20.8
	(30.15)	(35.79)	(30.92)	(25.8)	(21.29)
42	32.4	49.5	35.6	29.2	20.6
	(28.43)	(33.91)	(28.29)	(24.62)	(21.75)
49	31.1	46.7	34.5	28.3	19.7
	(27.22)	(32.54)	(28.49)	(22.89)	(20.3)
56	29.1	45.8	32.8	25.2	18.2
	(25.65)	(31.92)	(26.32)	(20.51)	(18.33)
63	30.5	43.9	33.1	28.5	20.7
	(25.77)	(30.24)	(27.42)	(22.27)	(19.79)
70	28.6	41.9	30.8	25.9	19.7
	(24.69)	(30.04)	(25.31)	(21.45)	(18.39)

(a) Average price across booking days, standard errors in parentheses.

(b) Price is a one-way fare, measured in British Sterling (£) excluding taxes and airport charges.

(c) For the definition of low competitive routes (Low Comp.) and highly competitive routes (High Comp.), see Section 6.2 of this paper.

U.K. Civil Aviation Authority provided daily data on all the flights operated by our two LCCs, Ryanair and EasyJet. This dataset contains information on the flight frequency, as well as on the number of passengers and the available seat capacity of each flight code departing on a given day. Constructing load factors from this data is a trivial exercise, where the number of final passengers is divided by the aircraft's capacity. In our dataset, the average load factor is 78 percent, with a standard deviation of 15.71 percent. The highly strategic nature of such information leads the Civil Aviation Authority to the decision to stop selling data with a daily frequency. Therefore, we also use monthly data, always from the U.K. Civil Aviation Authority, to identify the full set of competitors on the route, and to eventually classify the routes into those with high and low levels of competition (see section 6.2).

Finally, the third source we will use is the International Passenger Survey (IPS), which is prepared and managed by the U.K. Office for National Statistics and distributed via the U.K. Data Archive. The survey is a random sample of about 2 percent of passengers entering/leaving the U.K. by air. It provides quarterly information on expenditure levels and passenger characteristics, including the purpose of the journey. For each route, we aggregate the survey information across carriers to derive a set of measures indicating the percentage of passengers traveling for a specific reason (business, holiday, visiting friends & relatives). This enables us to determine whether passengers on a route are homogeneous (i.e., traveling predominantly on business of for pleasure) or heterogeneous (representing a mix of business and leisure traffic). As we will discuss below, we define routes as homogeneous if over two thirds of the passengers surveyed belonged to one of the broad categories (business or pleasure travelers). Most of the routes with homogeneous passenger demand represent leisure or tourist markets.

5 Econometric Model

The specification we will estimate is as follows:

$$\begin{aligned}\text{LoadFactor}_{ijmt} &= \beta_1 \text{AveragePrice}_{ijrmt} + \beta_2 \text{YieldManagement}_{ijrmt} + \\ &+ \delta_1 \text{Xmas}_t + \delta_2 \text{Easter}_t + \delta_3 \text{MidAugust}_t + \\ &+ \sum_{k=1}^{6} \gamma_k \text{Weekday}_{kt} + \rho_{ijrm} + \varepsilon_{ijrmt}\end{aligned} \tag{1}$$

Where t indexes time (day of the month), i represents a flight code operated by an airline j on route r in a given month m. Note that under this panel specification, market structure is given, therefore the fixed effect estimator guarantees our estimates not to be biased by any influence of competition.[8] The use of monthly panels also takes into account possible seasonal effects, which in turn may be associated with a particular choice of the pricing template.

The dependent variable, LoadFactor, is the flight's realized occupancy rate, previously defined.

The key variables of interests are AveragePrice and YieldManagement. The former is the simple average price of the 13 fares posted on the respective booking days (70, 63... 1 days before the flight's scheduled departure day). We use this measure to control for the 'general' (i.e., average) effect of fares on load factor. As one of our robustness checks, we will later recalculate this average price applying different weights to individual quotes.

YieldManagement variable measures the number of price drops during the booking period and thus aims to capture the effect of the yield manager's intervention. To focus on price drops that are clearly non-random, and realizing that, for early booking days, a single price drop may reflect the chosen pricing profile of a carrier's template, we define a sustained price drop in the following way. For booking dates from 70 to 21 days before the departure, price drop is identified as the instance of a lower fare quote for two consecutive dates of data collection. That is, we count a price drop if the fare P at time t is such that: $P_t \leq P_{t-1} - £5 \leq P_{t-2} - £5$. For booking days from 14 to 1 day prior to departure, any price drop counts, i.e., a price drop is recorded if $P_t \leq P_{t-1} - £5$. Thus, the price drop, in addition to being persistent over two early booking days, has to be also economically relevant, and be at least equal to $£5$.

From Table 2, the following stylized facts stand out. First, price can drop at any time before the flight departure date; the highest frequency of price decreases is observed between four and three weeks prior to departure, when quoted price drops for nearly three out of ten flights. Second, we are least likely to observe falling fare quotes within the last ten days prior to flight departure. Third, the relative magnitude of price decreases is not trivial - from nearly 25 to almost 60 percent of the fare[9]. Fourth, Easyjet on average exhibits smaller percentage price drops than Ryanair. Furthermore,

[8]This is because airlines keep their flight schedule fixed for a period which is usually longer than a month (typically airlines operate a winter schedule and a summer schedule).

[9]Recall, however, that we are only recording price drops higher than £5, which already represents 6 to 18 percent of the average fare quote

the intertemporal profile of the two carriers appears to be different; for each carrier, the percentage of flights with price drops varies across booking periods. Finally, the largest price drop observed in our sample is over £200; however, the distribution of price decreases is understandably skewed: e.g., the 90th and 95th percentile are respectively £40 and £60.

On average, we observe 1.12 sustained price drops per flight, with the standard deviation of 0.95. The highest number of sustained price drops in our sample is 7. About 30% of the flights in our sample have no sustained price drops, and there is no difference in this measure across the two carriers in our sample. Overall, about seven out of ten flights in our sample exhibit at least one sustained drop in the price quotes as the departure day nears.

Table 2: Price drops

Booking Days	Variables' list	Easyjet	Ryanair	Total
4-1	Average Price Drop , in %	-32.6	-37.7	-36.5
	Flights with price drops, in %	3.6	8.9	6.5
	Observations	28748	36563	65311
7-4	Average Price Drop , in %	-30.9	-35.4	-34.4
	Flights with price drops, in %	3.4	9.4	6.8
	Observations	54817	71363	126180
10-7	Average Price Drop , in %	-37.9	-41.4	-40.3
	Flights with price drops, in %	8.0	15.2	12.0
	Observations	52378	66892	119270
14-10	Average Price Drop , in %	-24.3	-38.5	-29.8
	Flights with price drops, in %	23.8	11.9	17.1
	Observations	54820	71371	126191
21-14	Average Price Drop , in %	-28.7	-46.1	-39.1
	Flights with price drops, in %	17.9	20.5	19.3
	Observations	54837	71367	126204
28-21	Average Price Drop , in %	-28.7	-49.9	-38.2
	Flights with price drops, in %	36.1	22.5	28.4
	Observations	54787	71129	125916
35-28	Average Price Drop , in %	-28.4	-51.0	-42.5
	Flights with price drops, in %	15.3	19.4	17.6
	Observations	54162	70933	125095
42-35	Average Price Drop , in %	-33.9	-52.8	-47.1
	Flights with price drops, in %	12.7	22.6	18.3
	Observations	54310	70687	124997
49-42	Average Price Drop , in %	-33.2	-52.3	-46.0
	Flights with price drops, in %	14.1	21.7	18.4
	Observations	53380	70943	124323
56-49	Average Price Drop , in %	-33.0	-53.7	-45.8
	Flights with price drops, in %	15.5	19.1	17.5
	Observations	52912	69513	122425
63-56	Average Price Drop , in %	-32.5	-58.4	-50.5
	Flights with price drops, in %	15.2	26.2	21.4
	Observations	53147	71066	124213
70-63	Average Price Drop , in %	-30.8	-56.4	-46.9
	Flights with price drops, in %	13.9	18.3	16.4
	Observations	51448	66451	117899

(a) Price Drop is defined as $P_t \leq P_{t-1} - £5$.

The remaining variables control for potential peak demand periods. Xmas, Easter and MidAugust are three indicator variables for flights departing during the week(s) of Christmas and New Year (winter peak), Easter (spring peak), and August 15th (summer peak), respectively.

Weekday variables are indicators for the day of the week, on which the flight is scheduled (with Wednesdays being the omitted category). Thus, the coefficients on these dummies show how different load factors are on average on a given day of the week relative to those for Wednesday flights.

The flight-code specific heterogeneity (e.g., Ryanair flight FR3768 from London Luton to Girona) will be captured by the corresponding flight-code fixed effects ρ_{ijrm}. Then, ε_{ijrmt} represents the idiosyncratic errors that may be correlated both serially and with errors for other observations within a route. To correctly account for these properties of disturbances in estimation, our standard errors will be clustered by route and week. This will capture the possibility of flight-specific demand shocks on a given day affecting the demand for all of the flights on the route in a given week. For instance, a large group booking for a Wednesday morning flight may raise fares for this flight, and lead to customers switching to other flights of the same airline on nearby days, or to flights of the competing carrier(s).

Our biggest econometric challenge comes from the fact that unobserved shocks affecting load factors will also affect the average price. Consequently, unobserved shocks affecting our dependent variable can also influence the implementation of YM by the airlines. Thus, since both of our key independent variables are correlated with the error term, we address this problem by using an instrumental variable approach.

We use the following variables as instruments:

- Price of jet fuel (obtained from the US Department of Transportation web site): this variable is an airline cost shifter. Using cost shifters as instruments for price is a standard practice.

- Number of booking days (NOT flight departure days) falling in the holiday period (weeks of Christmas, Easter, and August 15th). The airlines can expect fewer bookings on those days, which may affect their exercise of YM.

- Average number of price drops for the flights departing within the two weeks preceding and following the current week. For example, for a flight departing on a Monday, we construct this instrument as the average of fare drops for the same flight departing on the two previous and the two next Mondays. This exercise is in the spirit of using lags and leads of the endogenous variables as instruments. More importantly, this instrument is meant to purge the regressor of the effect induced by the carrier's use of a standard template on a given flight, as indicated in EU Competition Commission (2007), thus allowing the identification of the impact of idiosyncratic YM interventions. In other words, the instrument is likely to be correlated with the variable YieldManagement, but it should not be with ε_{ijrmt}, since the latter is unlikely to be influenced by shocks in demand that have affected one- or two-weeks old flights, and it is unlikely to influence similarly distanced future flights.

To confirm the validity of our instruments, we use the Hansen test for overidentifying restrictions. If the test fails to reject the null hypothesis, then all instruments used are considered exogenous. We will report this test in all the tables. To anticipate results, the Hansen test clearly supports our choice of instruments - the null hypothesis is never rejected at conventional significance levels. To demonstrate that the instruments we have chosen are not weak (that is, that they are actually correlated with the endogenous variables), first-stage regression results for the two-stage least squares estimation for some of our specifications are presented in Table 7 in the Appendix. This is done in addition to employing the Cragg and Donald (1993) test. This test has been suggested by Stock and Yogo (2005) as a test for the presence of weak instruments. This is essentially an F-test, with null hypothesis being underidentification - largely rejected in all our estimates.

6 Results

Our econometric strategy will be as follows. We will start by presenting results for the entire sample. Both the Generalized Least Squares (GLS) and Two-Stage Least Squares (2SLS) estimation results will be reported, to demonstrate that the use of the instrumental variable technique fundamentally changes the coefficients on the key independent variables. Next, we will examine whether the effect of YM on load factor depends on the level of competition and on consumer heterogeneity. A priori we expect a higher impact of YM on more competitive routes, and on markets with more heterogeneous customers, as demand on these routes will likely be more variable. Finally, we will use different measures of average offered price, as well as the simple range of offered prices, as robustness checks of our results.

6.1 Full Sample

This section presents the results of the data analysis, carried out according to the strategy outlined in the previous section of the paper. Estimation results of equation (1) for the entire sample are reported in Table 3. Column (1) reports the GLS Fixed Effects estimates, which are included primarily to gauge the impact of the instruments. To check for the presence of endogeneity we apply the Hausman (1978) test between the models "2SLS" and "GLS Fixed Effects". The test produces a χ^2 value equal to 21.42, which is statistically significant at a critical value below 5%; hence, we reject the null hypothesis of exogeneity. Cragg and Donald (1993) test results suggest that our instruments are not weak. Columns (2) and (3) in Table 3 report 2SLS fixed effects results. Column (3) presents results of the specification using the natural logarithm of load factor as dependent variable.

Relative to those in Column (1), the results reported in Column (2) demonstrate that there is a change in the sign and significance of the coefficient on the YM variable, when the instrumental variable technique is applied. When we do not account for endogeneity of this variable, we find that more price drops are associated with lower load factors. Such a negative correlation is consistent with the view that a larger number of price drops is likely to be observed in flights whose performance is worse than expected. However, as it is standard in these cases, the GLS is not consistently estimating the causal effect of the YM interventions. Indeed, the GLS estimates measures the difference in the expected load factors of two arbitrary flights with the same characteristics, except that their numbers of price drops differs by one unit. What we are interested in measuring is the expected load factor difference if on an arbitrary flight the yield manager (for some exogenous reasons) decides to increase the number of price drops by one unit.

Interestingly, when endogeneity is taken into account, the causal interpretation of YieldManagement is in accordance to our expected hypothesis: a price drop appears to be effective in raising the load factors. Furthermore, moving the attention to the other endogenous regressor, a higher average offered price is associated with higher load factors. This is in line with the theoretical predictions in Dana (1999b) that carriers ex-ante allocate seats into buckets (or fare classes) whose price increases as the plane fills up.

Table 3: Full sample estimates

	(1) GLS FE	(2) 2SLS FE	(3) 2SLS FE
Average price	0.270***	0.226***	0.003***
	(0.005)	(0.077)	(0.001)
Yield management	-0.229***	1.951**	0.039**
	(0.066)	(0.983)	(0.017)
Winter peak (Xmas)	0.548	1.048	0.009
	(0.657)	(1.792)	(0.029)
Spring peak (Easter)	1.049**	1.550	0.021
	(0.443)	(1.096)	(0.018)
Summer peak (Mid-August)	1.283***	1.034**	0.014**
	(0.338)	(0.449)	(0.007)
Sundays	0.916***	1.376	0.019
	(0.254)	(1.315)	(0.022)
Mondays	3.469***	3.970***	0.066***
	(0.205)	(0.830)	(0.014)
Tuesdays	0.183	0.257	0.005
	(0.168)	(0.204)	(0.004)
Thursdays	2.585***	2.679***	0.045***
	(0.160)	(0.467)	(0.008)
Fridays	2.252***	2.578**	0.037**
	(0.225)	(1.074)	(0.018)
Saturdays	1.755***	1.956**	0.034**
	(0.222)	(0.946)	(0.016)
R^2	0.148	0.127	0.084
Cragg-Donald F-stat		116.791	117.241
Hansen χ^2		1.909	2.333
Hansen p-value		0.167	0.127
Observations	109097	109079	109071

(a) Model (1) Generalized Least Squares Fixed-Effect. Models (2) and (3) Two-Stage Least Squares.

(b) Dependent variable: *Load factor* for Models (1) and (2), *log(Load factor)* for Model (3).

(c) Estimation technique: flight-code fixed effects with standard errors in parentheses, robust to heteroscedasticity and serial correlation, clustered by route-week.

(d) See text for the list of instruments for *Average price* and *Yield management*.

(e) Coefficients *** statistically significant at 1%, ** at 5% and *at 10%.

The magnitudes of the estimated effects of price and YM are as follows. Taking the coefficient on AveragePrice in the model “2SLS”of Column (2), an increase of AveragePrice by the interquartile difference (i.e., 3rd quartile - 1st quartile) is associated with a raise of LoadFactor by about 7 percent. Also (based on 2SLS result), one standard deviation increase in the YieldManagement variable raises LoadFactor by about 2 percent. Recalling that the standard deviation of our YM variable is close to 1, we can re-interpret our result as suggesting that an additional price drop increases load factor by about 2 percent. For a typical Ryanair’s 189-seat aircraft, this translates into about 3.8 additional seats sold as a result of the application of an YM approach aimed at lowering the offered price in response to unusually slow realization of demand, holding everything else - including average price - constant.

As far as the remaining control variables are concerned, we observe that load factors are higher on average on certain days of the week, and during some of the higher demand periods. More interestingly the positive sign found across the six dummy variables representing the day of the week suggests that flights to depart on Wednesdays have the lowest load factor.[10] For this reason, we will refer to this case as the “Wednesday-effect”. Finally, it is noteworthy that using a specification in log of the LoadFactor variable - Column (3) in Table 3 - does not alter the qualitative interpretations of the results.

The results reported in Table 3 provide the backdrop against which we investigate the central issue of the paper, namely, whether the effect of an intervention by a yield manager depends on the extent of competition, and on the degree of consumer heterogeneity in a route.

6.2 Competition and Consumer Heterogeneity

To address these questions, we recall that, within the same month, market structure is fixed. Similarly, as indicated in Gerardi and Shapiro (2009), travelers’ motivation remains constant over time, with some routes being predominantly used by leisure travelers, while others by a more heterogeneous mixture of passengers. To study both aspects, we re-estimate equation (1) for the following sub-samples. In the first categorization, we differentiate the sample according to the extent of competition on the market. Competition is measured using the number of airlines present both at the

[10] Recall that Wednesdays is the reference category of the day-of-the-week dummy group, and therefore the positive sign on the other dummies measures the average increase in the load factor of the observed day with respect to Wednesday.

route level and at the city-pair level, so that if a route is a monopoly within a very competitive city-pair, it is classified as competitive. We define a route as an airport pair (e.g., London Gatwick and Rome Fiumicino). A city-pair includes all the airports serving the two cities. Thus, a route may be operated by a single carrier, but the latter may face competition from other airlines operating in the same city-pair. We define a market to be highly competitive if there are at least three carriers on the city-pair market, and at least two airlines are present on the airport-pair market, or if the number of airlines present in the city-pair is larger than or equal to five, irrespective of the number of airlines serving the given airport-pair market. The average Herfindahl index across city-pair markets in this sub-sample of competitive routes is 0.28. By contrast, the city-pair market Herfindahl index for the sub-set of non-competitive markets is 0.56. The applied classification of markets between competitive and non-competitive splits our sample into two roughly equally sized sub-samples.

In the other categorization, we differentiate our sample with respect to the extent of demand heterogeneity, which we capture by considering the purpose of travel reported by interviewees participating to the U.K. International Passenger Survey. More precisely, for each quarter we measure the share of passengers reporting the following purpose for the journey: holiday and leisure, visiting friends & relatives, and business. We define a route to be homogeneous, if over two thirds of travelers on the respective city-pair market belong to either of the three categories of passengers identified above. Otherwise, we classify the market as heterogeneous. The two resulting sub-samples are again nearly equal in size; with the sub-sample for homogeneous market containing somewhat more observations. Most of the markets classified as homogeneous happen to be leisure/tourist routes.

The results of estimating equation (1) on the aforementioned subsamples are reported in table 4. Note that we only report 2SLS results in this table. Columns (1) and (2) include results for the sub-samples of non-competitive and competitive routes, respectively. Columns (3) and (4) report results for homogeneous and heterogeneous routes in terms of the passenger mix, respectively.

Focusing on competition, we observe that the coefficient on AveragePrice variable is only significant for non-competitive markets. Given the panel nature of our dataset, this result means that on markets we classified as competitive, LCCs' average fare quote levels do not affect the realized load factors; whereas on the non-competitive routes pricing does have an effect. This result is reminiscent of the 'price-taker' firm

Table 4: Different market conditions. Dependent variable: *Load factor*

	(1) Non Compet. Routes	(2) Competitive Routes	(3) Homog. Routes	(4) Heterog. Routes
Average price	0.296***	0.133	0.309***	0.139
	(0.104)	(0.120)	(0.103)	(0.108)
Yield management	-0.748	4.686***	-2.320	2.508**
	(1.384)	(1.534)	(2.142)	(1.016)
Winter peak (Xmas)	-1.176	2.397	-1.294	5.047**
	(3.062)	(2.128)	(2.414)	(2.405)
Spring peak (Easter)	0.462	2.664*	-0.555	3.386**
	(1.527)	(1.597)	(1.584)	(1.484)
Summer peak (Mid-August)	2.281***	0.206	1.676**	0.655
	(0.656)	(0.637)	(0.688)	(0.807)
Sundays	-1.747	4.968**	-0.343	3.509
	(1.843)	(1.951)	(1.542)	(2.285)
Mondays	1.730	5.988***	1.769	6.113***
	(1.259)	(1.130)	(1.149)	(1.341)
Tuesdays	0.074	0.352	-0.225	1.067***
	(0.288)	(0.300)	(0.322)	(0.327)
Thursdays	1.582**	3.704***	1.575***	3.735***
	(0.683)	(0.662)	(0.555)	(0.805)
Fridays	-0.503	5.576***	0.780	4.620***
	(1.522)	(1.566)	(1.236)	(1.762)
Saturdays	-0.917	4.834***	0.629	2.936**
	(1.420)	(1.266)	(1.246)	(1.360)
R^2	0.155	0.062	0.116	0.102
Cragg-Donald F-stat	54.336	64.875	22.822	113.558
Hansen χ^2	0.059	2.521	0.145	0.494
Hansen p-value	0.808	0.112	0.703	0.482
Observations	55382	53697	53347	40477

(a) Model (1) subsample of non-competitive routes, Model (2) subsample of competitive routes, Model (3) subsample of homogeneous routes, Model (4) subsample of heterogeneous routes.
(b) Estimation technique: flight-code fixed effects two-stage least squares with standard errors in parentheses, robust to heteroscedasticity and serial correlation, clustered by route-week.
(c) See text for discussion of instruments for *Average price* and *Yield management*.
(d) Coefficients *** statistically significant at 1%, ** at 5% and * at 10%.

on the competitive market versus the 'price-setter' firm with market power. Of course, an important qualification here is that the average fare quote is only an approximation of the actual prices paid by the travelers. Quantitatively, an interquartile difference increase of AveragePrice on the markets classified as not competitive is associated with a raise of the occupancy rate by 9.73 percent.

Our results also reveal that YM variable is not significant in non-competitive markets, whilst it has a significant impact on the competitive routes. This outcome is consistent with the idea that on competitive markets the airlines will use YM interventions to effectively steal market share from its competitors. For this reason, we will refer to this case as the "market-stealing effect". Specifically, one standard deviation increase in YM variable on markets classified as competitive is associated with about 4.4 percent increase in load factor. Coming back to our illustrative example of an 189-seat Ryanair flight, one price drop on a competitive market will lead to about 9.5 additional sold seats. Interestingly, even though price drops appear to be more effective on competitive routes, they are *not* more frequent on markets with a lot of competition as compared to routes with little competition. In fact, we observe about the same number of price drops on competitive and non-competitive routes, by our classification.

Columns (3) and (4) of table 4 report the results for sub-samples of homogeneous and heterogeneous routes, respectively.

In markets with highly homogeneous consumers (as we indicated above, this sub-sample is dominated by leisure/tourists markets) what drives the determination of the load factor is mainly the price level. Quantitatively, an interquartile difference increase of AveragePrice is associated with an increase of LoadFactor by 11.28 percent in homogeneous routes. This is consistent with the general wisdom that leisure passengers are price sensitive.

However, when demand heterogeneity is large, the YM variable becomes highly significant. Price change is a way meant to attract customers with a larger dispersion in their willingness to pay, which is unknown to the airline a priori. The price drops are thus probes to test current levels of demand. Note that the marginal effect of the YM variable is similar to that one for the whole sample: one standard deviation increase in the YM variable leads to about 2.4 percent increase in the realized load factor in the sub-sample of heterogeneous routes, versus 2 percent in the full sample. Interestingly, Christmas and Easter dummies are highly significant in the case of high demand heterogeneity, showing that the peak demand effect appears stronger when passengers are heterogeneous.

With respect to the day of the week indicator variables, we observe that the corresponding coefficients are mostly positive and significant in the sub-samples of competitive routes and markets with heterogeneous consumers. This suggests that the Wednesday-effect is also stronger on those markets.

6.3 Robustness Checks

6.3.1 General

The main results thus far are as follows.

- When we consider the entire sample, both average price and YM intervention positively and statistically significantly impact the realized load factors.
- When we split the sample according to the degree of competition between the airlines, it appears that the load factor is responsive to price but not to YM on non-competitive routes. On competitive markets, however, YM affects the load factor, and average price does not have a statistically significant effect. The estimates from the competitive markets suggest that the airlines may use YM to benefit from a market share stealing effect. Interestingly, even though YM as we define it is not as effective on non-competitive routes, it is not practiced less frequently on those markets, as compared to the markets in which competition among the airlines is high.
- When we focus on demand heterogeneity, the determination of the load factor in homogenous markets is mainly driven by the flight's price level, whilst when demand heterogeneity is large, the YM variable becomes highly statistically significant; that is, YM appears more effective with a larger dispersion in the passengers' willingness to pay.

In this subsection we will implement the following two robustness checks:

- Use a weighted average offered fare instead of the simple average fare. Since the distribution of passengers purchasing their ticket may vary across the booking periods (for instance, more tickets might be bought closer to the flight departure date than further away from it, or vice versa), we assume different demand distributions across booking days (i.e., we assign different weights to each offered fare in different booking days), and re-calculate the average offered prices accordingly. This also addresses the issue of potential interpretation of our measure of YM as a way to implement inter-temporal price discrimination. As we noted above, price drops closer to the departure date are most likely to represent exercise of YM, so stronger relationship between price drops and load factors in regressions putting more weight on observations closer to the flight departure date will strengthen our story.

- Replace the average price with FareGap, i.e., the difference between the highest and the lowest fare quotes for a given flight on a given date. This variable aims to capture elements of the second moment in the distribution of fares.

6.3.2 Weighted Average Price

The major difference among the four models in Table 5 lies in the degree of importance assigned to fare quotes observed closer to the flight date. Specifically, Model (1) in Table 5 assigns a 20% cumulative weight to early booking period (booking days 70-49), a 40% one to middle booking period (booking days 42-14), and a 40% one to late booking period (10-1 booking days). Model (2)'s weights are: 30% for early booking period, 40% for middle booking period, and 30% for late booking period. Next, Model (3) computes weighted average assigning 35% to early, 40% to middle, and 25% to late booking periods. Finally, Model (4)'s weights for the three booking periods are 40%, 40%, and 20%, respectively. That is, as we shift from Model (1) towards Model (4) we give more weight to the early booking period and less weight to the late booking period in calculation of the weighted average fare.

We can clearly see that changing the weights of the fare quotes in calculating the average offered price does not in any fundamental way affect the previously reported results for our key variables. Further, our reweighing does not qualitatively change the effect of average price on load factor. However, note that the estimated effect of YM interventions is quantitatively stronger the higher the weight given to the late quotes in the calculation of mean offered price. This finding appears to reflect the fact that price drops are more frequent the further away from the departure date the drop is implemented. When fare quotes at the time price drops occur more regularly are not weighed heavily, the effect of price decreases stands out more profoundly.

Table 5: Weighted average price. Dependent Variable: *Load factor*

	(1)	(2)	(3)	(4)
Weighted average price	0.227***	0.240***	0.247***	0.254***
	(0.076)	(0.080)	(0.082)	(0.085)
Yield management	2.310***	2.057**	1.920**	1.776*
	(0.884)	(0.943)	(0.977)	(1.015)
Winter peak (Xmas)	0.892	0.608	0.455	0.295
	(1.807)	(1.899)	(1.950)	(2.005)
Spring peak (Easter)	1.409	1.289	1.225	1.159
	(1.110)	(1.150)	(1.172)	(1.195)
Summer peak (Mid-August)	1.121**	1.091**	1.074**	1.056**
	(0.463)	(0.456)	(0.453)	(0.449)
Sundays	0.988	0.939	0.914	0.888
	(1.411)	(1.428)	(1.438)	(1.449)
Mondays	3.730***	3.714***	3.706***	3.699***
	(0.889)	(0.894)	(0.898)	(0.901)
Tuesdays	0.222	0.216	0.213	0.210
	(0.207)	(0.209)	(0.210)	(0.211)
Thursdays	2.564***	2.555***	2.550***	2.546***
	(0.492)	(0.495)	(0.497)	(0.499)
Fridays	2.301**	2.263**	2.243*	2.224*
	(1.139)	(1.152)	(1.159)	(1.167)
Saturdays	1.802*	1.708*	1.658	1.607
	(0.974)	(1.004)	(1.021)	(1.039)
R^2	0.151	0.141	0.134	0.126
Cragg-Donald F-stat	97.484	100.692	101.607	101.927
Hansen χ^2	1.834	1.741	1.691	1.639
Hansen p-value	0.176	0.187	0.193	0.200
Observations	109079	109079	109079	109079

(a) Models (1)-(4) differ in weights used in calculation of average price. See text for description.

(b) Estimation technique: flight-code fixed effects two-stage least squares with standard errors in parentheses, robust to heteroscedasticity and serial correlation, clustered by route-week.

(c) Same instruments were used as elsewhere in the paper.

(d) Coefficients *** statistically significant at 1%, ** at 5% and * at 10%.

6.3.3 Using price range instead of average price

Table 6 reports estimation results of our specification, where AveragePrice is replaced with the variable FareGap, i.e., the difference between the highest and the lowest fare quotes for a given flight on a given date. We can expect that average offered price might not capture the impact of the airline's pricing policy on the realized load factor. By keeping the price low initially and increasing it to higher levels later on when the price insensitive customers show up, the airline might be able to achieve higher load factors than it would be by keeping the price constant as the departure date approaches. Alternatively, high fare gap means that seats in the lower-priced categories have been sold out, and the airline has for this particular flight been selling more expensive seats, presumably closer to the date of the flight departure.

We generally expect a positive sign on the FareGap variable. Since price range can also be correlated with the error term, we employ the same instrumental variable approach as elsewhere in this study, and report 2SLS fixed effects results in Table 6.

When we replace the average price with the range of offered fares, we see the following changes in our estimation results. First, the range of fare quotes significantly affects load factor not only for the entire sample, but also for all the sub-samples employed. Recall that we did not observe any significant effect of average price for the sub-samples of non-competitive and heterogeneous routes. Notably, the estimated effect of range of fare quotes remains higher in the non-competitive markets sub-sample. As far as the effect of yield management is concerned, we continue not to observe any statistically important association for the non-competitive routes sub-sample. The coefficient of the YM variable is the largest in the sub-sample of competitive routes, thereby supporting the previous results that YM may play a crucial role as an effective competitive strategy. Differentiation of routes in terms of consumer heterogeneity, at the same time, no longer produces strikingly different results, judging by the relative magnitudes of the corresponding coefficients on YM variable. We also note that the magnitude of the YM variable coefficients for the entire sample, and for sub-samples of competitive and heterogeneous markets is very similar to what we have obtained previously.

Table 6: Fare gap (Max - min fares). Dependent variable: *Load factor*

	(1) Full Sample	(2) Non Compet. Routes	(3) Competitive Routes	(4) Homog. Routes	(5) Heterog. Routes
Fare gap	0.173***	0.196***	0.140***	0.182***	0.148***
	(0.011)	(0.014)	(0.015)	(0.018)	(0.015)
Yield management	2.957***	1.172	4.795***	2.237**	2.141**
	(0.704)	(1.016)	(1.022)	(1.138)	(0.941)
Winter peak (Xmas)	4.140***	4.304***	3.652***	3.487***	6.002***
	(0.646)	(0.833)	(0.961)	(0.940)	(0.949)
Spring peak (Easter)	3.664***	3.644***	3.608***	2.987***	4.405***
	(0.456)	(0.581)	(0.726)	(0.614)	(0.803)
Summer peak (Mid-August)	0.883**	1.122**	0.653	0.945*	0.666
	(0.402)	(0.497)	(0.584)	(0.556)	(0.718)
Sundays	2.617***	1.193***	4.506***	1.865***	3.791***
	(0.291)	(0.362)	(0.456)	(0.362)	(0.508)
Mondays	4.630***	3.354***	5.838***	3.549***	5.950***
	(0.232)	(0.292)	(0.352)	(0.302)	(0.395)
Tuesdays	0.585***	0.603***	0.509**	0.439**	1.192***
	(0.172)	(0.228)	(0.259)	(0.220)	(0.291)
Thursdays	2.778***	2.144***	3.403***	2.112***	3.484***
	(0.188)	(0.255)	(0.266)	(0.241)	(0.332)
Fridays	3.367***	1.560***	5.206***	2.177***	4.727***
	(0.270)	(0.349)	(0.401)	(0.366)	(0.441)
Saturdays	3.081***	1.527***	4.787***	2.571***	3.259***
	(0.278)	(0.342)	(0.439)	(0.383)	(0.460)
R^2	0.108	0.125	0.084	0.111	0.133
Cragg-Donald F-stat	336.814	158.223	179.957	99.620	207.433
Hansen χ^2	4.651	1.617	4.996	3.312	1.389
Hansen p-value	0.098	0.446	0.082	0.191	0.499
Observations	109079	55382	53697	53347	40477

(a) Models: (1) - full sample; (2) - subsample of non-competitive routes; (3) - subsample of competitive routes; (4) - subsample of homogeneous routes; (5) - subsample of heterogeneous routes.

(b) Estimation technique: flight-code fixed effects two-stage least squares with standard errors in parentheses, robust to heteroscedasticity and serial correlation, clustered by route-week.

(c) Same instruments were used as elsewhere in the paper.

(d) Coefficients *** statistically significant at 1%, ** at 5% and * at 10%.

7 Conclusions

This paper offers the first empirical study of the effectiveness of yield management in the airline industry. We demonstrate that the practice of adjusting fares and seat inventories is effective in increasing the flight load factors; we quantify this effect, and determine whether it depends on some broadly defined market characteristics. We combine information on the evolution of offered priced as the flight departure day approaches with the data on realized load factors for over 100,000 unique flights on over 100 routes over one year. A unique feature of our dataset is that it comes from the European low-cost carriers. These airlines focus on direct flights, do not incorporate network consideration into their pricing strategy, sell all their tickets as strictly non-refundable contracts, and do not price discriminate between passengers traveling one-way versus round-trip.

We thus observe price quotes in an environment most closely resembling the theoretical exposition of pricing under fixed capacity and uncertain demand. We pick the most straightforward indicator of yield management - drops in fare quotes as the departure date nears. Price drop is a clear indication that demand realization does not proceed as expected, requiring involvement of a yield manager. The reason for picking the most obvious indicator of yield management (instead of evaluating how different the price path for a particular flight is relative to some estimated 'average' pricing profile) is simple. If we fail to observe effectiveness of this technique where it is definitely applied, then we can be quite certain that yield management is not very helpful. If we however see that the yield manager is able to increase the realized load factor by dropping the fare quotes, then this result opens the door to future research on the issue.

We indeed detect that exercise of yield management (as defined in our study) by the airlines leads to higher load factor. Specifically, one standard deviation increase in the yield management variable raises load factor by about 2 percent. Yield management appears to be more effective on more competitive routes, and on markets with heterogeneous consumers. The former result is however somewhat more robust than the latter. On competitive routes, one standard deviation increase in yield management variable is associated with nearly 5 percent increase in load factor.

We must note that, even though our paper reports evidence supporting effectiveness of yield management, an important qualification of our results is that we do not rule out intertemporal price discrimination. Our findings do not mean that the airlines do not price discriminate. Nor can we confidently state that we have been able to investigate the effect of different manifestations of yield management presented in the literature. Indeed, we have only focused on instances where this technique is clearly visible in our data. We leave the question of whether and to what degree the airlines price discriminate open; addressing this issue will probably require more detailed data than what we have now.

Our study is the first exploration of effectiveness of a pricing technique known to be used in the important and visible airline industry. Yield management is also applicable to, and used by, although to somewhat less extent, railroads, hotels, and rental car companies. Empirical analysis of this phenomenon is lacking, and will both help firms apply yield management more effectively, and shed light on the extent to which price dispersion in the relevant industries is the result of price discrimination. Ultimately, our study is beginning to address the clearly policy relevant question of the extent of exercise of market power in industries characterized by fixed short-run capacity and uncertain demand.

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Appendix

Table 7: First-stage estimates

	(1) Av. Price	(2) Yield Man.	(3) Av. Price	(4) Yield Man.
Winter peak (Xmas)	24.451***	0.238***	19.636***	0.292***
	(1.224)	(0.038)	(1.475)	(0.046)
Spring peak (Easter)	11.931***	0.004	11.125***	0.039
	(0.688)	(0.028)	(0.882)	(0.047)
Summer peak (Mid-August)	-3.292***	0.049	-2.853***	0.004
	(0.406)	(0.038)	(0.515)	(0.051)
Sundays	17.656***	0.115***	17.028***	0.131***
	(0.344)	(0.015)	(0.494)	(0.022)
Mondays	9.869***	-0.024*	8.609***	0.010
	(0.229)	(0.013)	(0.311)	(0.017)
Tuesdays	0.958***	-0.009	0.844***	0.012
	(0.138)	(0.011)	(0.175)	(0.014)
Thursdays	5.731***	0.063***	5.387***	0.091***
	(0.148)	(0.011)	(0.197)	(0.015)
Fridays	14.042***	0.115***	13.451***	0.160***
	(0.251)	(0.013)	(0.335)	(0.019)
Saturdays	12.824***	0.138***	11.305***	0.183***
	(0.292)	(0.014)	(0.413)	(0.019)
Jet fuel	0.191***	-0.004	0.189*	0.006*
	(0.070)	(0.003)	(0.099)	(0.003)
Average price falls	17.385***	2.367***	21.986***	2.509***
	(2.249)	(0.126)	(3.230)	(0.176)
Holiday period	-1.561***	-0.021***	-1.521***	-0.014
	(0.167)	(0.008)	(0.196)	(0.011)
R^2	0.204	0.024	0.215	0.030
Observations	109079	109079	53697	53697

(a) Columns (1) and (2) are first-stage estimates of Model (2) in table 3; Columns (3) and (4) are first-stage estimates of Model (2) in table 4.
(b) The regressions include flight-code fixed effects. Robust standard errors to heteroscedasticity and serial correlation in parentheses, clustered by route-week.
(c) Coefficients *** statistically significant at 1%, ** at 5% and *at 10%.