Targeting leisure and business passengers with unsegmented pricing*

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Abstract

We analyze the fare setting strategy of a leading European low-cost carrier, Ryanair, which, until recently, adopted an unsegmented pricing policy (all tickets belong to a single fare class). We show that, to account for different demand characteristics, the company adjusts the two main components governing the dynamics of posted fares, namely *time* (the number of days before departure) and *capacity* (the current number of available seats). We find that: 1) in routes with a strong presence of leisure (business) traffic, fares are set to be less (more) responsive to the time component; 2) in schedules more suitable for leisure (business) travellers, fares are set to be less (more) responsive to the capacity component.

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1 Introduction

Low-cost carriers have changed the airline industry, by proposing a business model that is based on a cost leadership strategy. Such an approach has become a marketing lever that credibly promotes a brand image based on the strong adherence to the low-cost concept, which implies that the firm strives to be never knowingly undersold by its competitors.

As a cost advantage normally derives from the exploitation of scale economies and learning effects, a cost leader company usually sells a "standardized, no-frills product" (Porter, 1985: 13). The most obvious limitation of standardization is that the firm may not be able to attract those demand segments with a high willingness to pay for a differentiated product or a personalized service. Nonetheless, there is evidence that an increasing number of business travellers choose low-cost carriers. How can these companies accomodate customer segmentation, in an unsegmented pricing setting?

The way firms address this problem is often industry-specific. For supermarkets, it is relatively easy to simply expand the range of products to include higher quality labels, such as the "Taste the Difference" one used by Sainsbury's, a leading UK supermarket. This may not be sufficient for other companies. For example Ikea, which offers the same type of furniture (say, a table or a sofa) in different ranges, still faces the problem that some customers may be put off by the need to self-assemble the items they buy. To address this issue, Ikea has developed a specific service of furniture assembly for time-constrained customers. This paper aims to highlight the crucial role of revenue management to face this issue in the airline industry. To gain a better understanding of such a role, it is however necessary to obtain information which companies tend to be reluctant to disclose, a factor that may explain the large gap in the literature on this issue.

In this study we propose an in-depth analysis of the Revenue Management (RM) system implemented by the leading European low-cost airline, Ryanair. RM constitutes a central organizational function in companies that have to set the prices of highly perishable services under uncertainty (McGill and Van Ryzin, 1999). It encompasses a set of processes and techniques that are ultimately responsible for the price offered to the final consumers. Our analysis is made possible by the acquisition of online information on aspects of RM that airlines tend not to reveal, which we complement with official statistics on market characteristics.

We illustrate the main pricing strategies adopted by an airline's RM system, and continue by discussing how these can be used to derive the testable hypotheses for our econometric work. Our analysis focuses on a situation where the company faces the opportunity to serve different markets, each characterized by a varying mix of leisure and business travellers, but is constrained by its commitment to an unsegmented pricing policy that imposes the use of a single fare class, the equivalent of a standardized service in the airline industry. Traditional do not face such a constraint, and can therefore set different class categories.

We report evidence indicating that Ryanair adapts its RM techniques to the market's characteristics, thus effectively carrying out a segmentation strategy. In practice, the two main components governing the dynamic of posted fares, namely *time* (the number of days before departure) and *capacity* (the current number of available seats), are adjusted to account for different compositions in demand characteristics. We find that: 1) in routes with a strong presence of leisure (business) traffic, fares are set to be less (more) responsive to the time component; 2) in schedules more suitable for leisure (business) travellers, fares are set to be less (more) responsive to the capacity component.

Our result confirms and complements the previous works on low-cost airline pricing and passenger characteristics by Malighetti et al. (2010) and Salanti et al. (2012), where, however, the analysis is restricted to the time component dimension. To our best knowledge there is no existing evidence exploring the link between the differentiated use of the capacity component to target consumers in different departing hours. However, Teichert et al. (2008) prove the utility of using different dimensions to account for passengers' differences.

The rest of the paper is organized as follows. In Sections 2 and 3 we briefly review the airline literature on revenue management and we provide the main hypotheses to be evaluated. Section 4 describes the data and offers some preliminary results. Section 5 introduces the econometric model. Section 6 provides the econometric evidence and Section 7 discusses and concludes the paper.

2 Revenue management in theory and practice

McGill and Van Ryzin (1999) identify four key areas for RM in the airline sector: forecasting, overbooking, seat inventory control and pricing. Forecasting plays a critical role in predicting the probability of different states of demand but it is an antecedent process that is largely reflected in the implementation of the other three components; overbooking is the practice of selling a number of tickets larger than the available seats accounting for the fact that some passenger show up for the flight. It is more often employed by Full-Service Carriers (henceforth, FCCs) than LCCs. The two remaining components are paramount in this work, since they are closely examined in the empirical section.

Seat inventory control defines the availability of seats for different booking classes. Even if the airline adopts unsegmented pricing and sells only one fare class with tickets of the same homogenous characteristics, it is still possible for the airline to pre-assign seats with different fare levels to distinct 'buckets', each denoting a group of consecutive seats that the airline wants to sell at a given price. In line with the work by Talluri and van Rizyn (2004), the airline decides the buckets' size (i.e., the number of seats in a bucket) as well as their fare level ex-ante when a flight is first put on sale, based on its demand forecast. The outcome is a full pricing plan for all seats on sale, detailing how the fare will change as the plane fills up. Based on the theoretical model in Dana (1999a), the optimal pricing plan is monotonically increasing because the cost of a seat varies inversely with the probability of selling it.

To test whether the airlines in practice follow this recommendation, it is necessary to know the load factor at the time a fare is posted. Such an information is generally proprietary and very secretive, but Alderighi et al. (2014), Clark and Vincent (2012), and Escobari (2012) used online data to overcome this difficulty. Their empirical findings provide strong support to the notion that fares increase as a plane fills up. Dana (1999a) also predicts that the price dispersion generated by the optimal pricing plan is larger in more competitive routes. Alderighi et al. (2014) test this prediction by looking at the slope of Ryanair's pricing plan, and find it is on average steeper (i.e., more dispersed) in less competitive routes.

Dana (1999b) offers another, complementary explanation as to why the slope of the pricing plan may vary to generate an efficient equilibrium response to uncertainty about the distribution of consumers' departure time preferences. For instance, it is generally assumed that it is more costly for business traveller to choose a flight departing at an inconvenient time. If there is uncertainty on which of two flights will have peak demand, the airline can profitably alter the mix of low and high price seats and exploit the fact that lower-priced units stock out at the peak time before they stock out at the off-peak time. Conversely, if it is highly likely that a flight will be the off-peak one, then it is profitable to increase the number of low-priced seats to induce some consumers, who would prefer to flight at an alternative time, to switch flight.

Pricing, the fourth component of RM, is strongly intertwined with seat inventory. In particular, to test whether a carrier engages in inter-temporal price discrimination, it is necessary to control that any change in fares over time is not simply induced by the evolution of the flight's load factor. The theoretical literature on Advance Purchase Discounts (APD) has identified customers' heterogeneity in terms of demand uncertainty as the main reason why the airlines may want to change their fares over time. Individuals with different travel motivation learn about their need to travel at various intervals before the actual travel date; notably, business travellers are very likely to book a flight very close of its actual departure, while leisure travellers tend to plan well in advance.

Because travel motivation is not observable by the carrier, APD provide a simple way to screen consumers by their demand uncertainty. Gale and Holmes (1993) demonstrate that in a monopoly with capacity constraints and perfectly predictable demand, APD form an efficient mechanism to carry out second degree price discrimination because they are used to separate customers with different evaluation of the flight: only the high-type will buy the non-discounted fares, while the low-types, anticipating the price hike, will make arrangements to book as soon as their need to travel is revealed. By doing so, the airlines price discriminate across customers on the basis of their price elasticity and time valuation. Möller and Watanabe (2010) compare APD (where prices are increasing over time) with clearance sales (where prices decrease over time), and illustrate how the former are more appropriate when a consumer faces no or little risk of being rationed.

One often observed way to manage the complexity of dealing simultaneously with all of the above aspects is to offer a portfolio of segmented fare categories, from economy to business, each with a different set of tickets and in-flight characteristics (free meal, refundability, cancellation, change of dates, etc). This is typically what traditional carriers do. Our empirical strategy is aimed at shedding light on how the same RM problems were tackled by a prominent low-cost carrier committed to an unsegmented pricing policy.

3 Hypotheses

The previous discussion has highlighted two important drivers of airline fares: inter-temporal price discrimination and the aircraft seat availability. In the remainder of the paper, the former will be referred to as the 'time component', and the latter as the 'capacity component'. Both components are under the control of a revenue manager; both are assumed to be adjusted to account for the mix of customer types in a market. The joint empirical investigation of the hypotheses developed in this section should therefore provide some indication of how a carrier's RM system can be effectively used to appropriate the value created by a higher-level low-cost strategy, even in circumstances where varying market conditions may be managed via the application of a single pricing policy.

Leisure and business travellers differ along two dimensions. First, business travellers usually assign a greater value to a flight and therefore their demand is more price inelastic than that of leisure travellers. Second, business travellers tend to plan less in advance than leisure ones (Talluri and van Ryzin, 2004). Therefore, heterogeneity between the two traveller segments allows to inter-temporally segment the market, applying higher fares to clients arriving late, mostly business travellers; and cheaper fares to those arriving early, mostly leisure travellers (Desiraju and Shugan, 1999; Courty, 2003; Netessine, 2006). When the share of business travellers is high (i.e., on a business route), the carrier will therefore tend to choose a pricing profile with large price hikes in the proximity of the departure date.

Hypothesis 1 *(leisure/business routes): on leisure (business) routes, fares tend to be less (more) strongly affected by the time component of RM.*

Flights early in the morning (6am-10am) or late in the evening (6pm-10pm) in the week days (i.e. in a business time) are appealing for business travellers (Borenstein and Netz, 1999). Indeed, they allow to easily visit a destination within a working day, i.e., departure in the morning with the return scheduled in the evening. Leisure travellers usually prefer a more comfortable schedule and generally have more flexible preferences in terms of departure date and time. As a result, the demand of the leisure segment is more price elastic due to the larger substitutability between flights across routes, departure dates and departure and arrival times.

Because the wide majority of LCCs' customers travel for leisure purposes, and network considerations make it necessary to operate flights at 'inconvenient times' for them, the carrier faces the problem of inducing some of the leisure travellers to choose flights operated during business hours. Based on Dana (1999b), one way to achieve this is by modifying the slope of the pricing plan; in business hours, the first buckets of seats should be assigned a lower than average fare level, to attract leisure passengers, while the last buckets should be priced significantly higher since they will be most likely sold to business customers whose need to purchase is revealed only once the flight is sufficiently full. In leisure time flights, because the expected demand is high, the carrier can achieve a higher yield by setting a higher fare for the first buckets, without increasing its fares too sharply for the last buckets. The upsides of such a strategy are that the carrier guarantees itself a smoother occupancy rate across the two types of flights (business vs. leisure hour) with higher occupancy rates also in the off-peak period (business time), as well as higher fares when unexpected high demand materialises, e.g., if and when business travellers choose their most convenient flight.

Hypothesis 2 *(leisure/business hours): In leisure (business) hour flights, the capacity component of RM, where fares depend on the remaining seats in a flight, tends to be less (more) prominent.*

Finally, as the route and hour dimensions concern different unrelated aspects of fight supply, we expect the carrier to independently use these two pricing policies.

Hypothesis 3 *(leisure/business routes and hours): For flights in both leisure (business) routes and hours, the capacity and time components of RM tend to be less (more) jointly prominent; in mixed cases (e.g., business routes and leisure hours), the dominant component is consistent with Hypotheses 1 and 2 (see: Figure 1).*

4 A business case: Ryanair

4.1 Ryanair's business model

Since the deregulation of the US and European airline sector, LCCs have gained considerable traffic volumes at the expenses of FSCs and regional carriers (Barrett, 2011). According to the International Civil Aviation Organization (ICAO), in 2012 LCCs supplied about one third of the overall seat capacity on continental routes both in U.S. (31%) and in Europe (37%).

By adopting the business model pioneered by Southwest Airlines, Ryanair rapidly became Europe's largest carrier and it established its clear low-cost 'firm identity' based on "continued improvements and expanded offerings of its low-fares service... while maintaining a continuous focus on cost-containment and operating efficiencies" (www.ryanair.com/doc/investor/Strategy.pdf).[1] Indeed, all the characteristics which allow a carrier to get and maintain a cost leadership strategy in the airline sector are indeed satisfied (Alamari and Fagan, 2005; Bilotkach et al., 2010): one type of aircraft, secondary airports, quick boarding time, high number of rotations, web-based selling strategy, no loyalty scheme, automated check-in, no food, no premium cabin, no connection guaranties, one class of tickets without price discrimination based on multiple service and cabin classes, no specific restrictions like minimum stay requirements and Saturday night stay-over, no overbooking. These features define Ryanair's business model, a model which heavily contrasts with that of FSCs, based on a number of customized services, such as business client support, business and economy cabins, free on

[1] With 81.4 millon scheduled passengers carried on international routes in 2013, it far outperformed its direct competitor easyJet (52.8 m) but also the larger full-service European carriers: Lufthansa (50.7 m), British Airways (33.8m), Air France (33.1m) and KLM (26.6m). Ranking first globally for scheduled passengers carried on international routes, it ranks 6th when considering both domestic and international flights, after Delta, Southwest, China Southern, United and American Airlines. Although its flights are mostly short to medium haul, Ryanair appears in the 7th position of the international scheduled passenger - kilometers flown list (IATA, 2013). With an increasing fleet, despite the rise in fuel costs, Ryanair has managed to steadily increase its operating revenue and net profit after tax (Ryanair, 2014).

board services, selective VIP lounge access, travel restrictions, multiple reservation classes, multiple fares simultaneously available, etc.

These striking differences are also reflected in the way the two types of carriers design their RM systems (Malighetti et al., 2009). Ryanair's fare structure is simpler than that adopted by FSCs, an aspect that by itself supports the view of a necessary coordination between a firm's higher-level strategy and its pricing system: up until mid-2014, it adopted only one reservation class, and consequently, one single fare which is intended for all customers (unsegmented pricing). It also rules out travel agents' commissions, connecting flights, code-sharing agreements and frequent flyers' programmes. FSCs' fare structure is much more complex: it usually includes 11-13 different reservation classes which accounts for different ground and in-flight services and flexibility requirements (segmented pricing). This differentiation strategy is an instrument to more easily segment the market and target business travellers (Cento, 2009). Nonetheless, it might not be sufficient, given the increased heterogeneity in customers' preferences (Teichert et al., 2008).

4.2 Ryanair's strategic positioning

Ryanair's choice of keeping its RM system as simple as possible has promoted the fidelization of leisure passengers (Hsu, 2006); however, Ryanair's network covers many non-strictly leisure markets where it faces a strong financial incentive to design a competitive strategy aimed at attracting business travellers, whose willingness to pay is generally considered to be higher than the market average. Thus, the company faces the dilemma of maintaining its core commitment to low fares without compromising its well-established firm identity.

Ryanair's strategic positioning as an exemplary LCC is beyond discussion and has been consistently pursued throughout its history: over the years, it has continued to adhere strictly to a cost leadership strategy (Porter, 1980, 1985; Barrett, 2011), offering a "no-frills service" (Porter, 1985: 13) combined with an "aggressive pricing" strategy (Porter, 1980: 36). The main consequence is that leisure travellers have formed its largest market demand segment. As its network expanded, so as to cover many capital cities and important economic areas, the number of non-strictly leisure destinations also grew, and with it the opportunity to tap into the profitable demand segment of business travellers, whose willingness to fly low-cost was, at least partly, motivated by private companies' travel policies aiming at containing costs but also by the high punctuality that many LCCs, and Ryanair in particular, have guaranteed (Dobson and Piga, 2013).

Given its great prolonged success, it seems unlikely that Ryanair did not attempt to take advantage of such an opportunity, even within the constraints imposed by the low-cost business model, and in particular by the standardization of its fares implied by the unsegmented pricing approach. In line with the approach discussed above, we hypothesize the carrier responded by adjusting its pricing policy (i.e., its RM system) in those markets with a higher potential demand by business travellers. A closer investigation of Ryanair's standard fares offers therefore an invaluable opportunity to gain insights into the capability role played by a company's pricing system, its compatibility with the company's wider strategy and its ability to set prices that can be effectively used to extract value from premium customers, even when the wider strategy does not explicitly considers segmentation as one of its objectives (Porter, 1980, 1985).

5 Data

5.1 Experimental design

The data used in the study derive from two different sources. Primary data on repeated prices for single flights and their characteristics were retrieved directly from Ryanair's website using a web crawler, i.e., a programme that automatically launches the online queries necessary to book a flight to a given destination. Secondary data detailing the composition of a route's passengers by reason of travel (leisure vs. business) were obtained from the International Passenger Survey (henceforth, IPS), a quarterly survey collected by the UK Office of National Statistics.

We consider only flights operated by Ryanair departing from an airport within the UK, and arriving at either a domestic or an international airport in one of the following countries: Austria, Belgium, France, Germany, Ireland, Italy, the Netherlands, Norway, Spain, Sweden over the period January 2004 - June 2005. The collection strategy exploited a feature of Ryanair's website: during the sample period, it was possible to purchase up to 50 seats using a single query.[2] Therefore, at the time of a query one could learn the exact number of available seats (up to 50) on a flight; this information is central for the identification of the capacity component of RM.

The web crawler, after issuing a query, retrieved all the information shown on the returned web page. To obtain information regarding the seat availability of a flight at a specific point in time, the web crawler followed this algorithm based on three steps.

[2]This is no longer possible, as the query can be for a maximum of 25 seats as of September 2014. However, the mechanism illustrated here still applies.

Step 1. Issue a query for 50 seats for a specific flight. The flight is due to depart D days from the date of the query, where D assumes the following values: 1, 4, 7, 10, 14, 21, 28, 35, 42, 49, 56, 63 and 70. The variable containing the information on the days to departure is labelled *BookingDay* in the subsequent analysis.

Step 2. If the airline's site returns a valid fare, this can be interpreted as follows: "D booking days prior to departure, there are at least 50 seats available on the flight". In this case we can not retrieve any more precise information regarding the observed number of available seats, which is thus censored at the level of 50. We store this information in a variable labelled *AvailableSeats*, which in this case assumes the value of 50. We also retain the corresponding value of the fare posted for the query of 50 seats, which we label *TopFare*. Additionally, we collect the information on the fare for a single seat, which is saved in the *Fare* variable. Finally, we store the value of *BookingDay* and all the other flight's details (see below).

Step 3. If the site fails to return a valid fare for that flight, the web crawler infers that there are fewer than 50 seats available. It then searches the highest number of seats in a query that returns a valid fare. This value defines the number of seats available D days before a flight's departure; it is stored in *AvailableSeats*. In this case, *TopFare* corresponds to the unit price at which the airline was willing to sell all the remaining seats in a single transaction. As in the previous case, we also store the fare for a single seat in *Fare*.

By repeating this procedure every day, we track the seats and the associated fares (both *Fare* and *TopFare*) of a flight at specific time intervals defined by *BookingDay*. Given our experimental design, for every daily flight we have up to 13 prices charged on different days before the day of departure, which allow the identification of the evolution of fares over time (time component of RM in Hypothesis 1).

5.2 Data structure

The web crawler also saved the departure date, the scheduled departure and arrival time, the origin and destination airports and the flight identification code. These variables are combined to obtain the panel identifier, which corresponds to a single flight between two destinations at a given time of the day on a specific day during January 2004 - June 2005. The time dimension of the panel is given by the time before departure (i.e., the booking day).

As we need to classify the routes according to the predominant type of customers, we use the data provided by the IPS database: it contains a random sample of around 2 percent of passengers entering/leaving the U.K. by air and 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 measure the percentage of passengers traveling for a specific reason (business or leisure). Such information is used to determine the passenger mix on the route, and then to classify flights into different routes categories.

After merging this information, we end up with data for 42 of the 154 routes that Ryanair operated to these countries over the sample period; in some cases, we consider more than one flight code per route when the airline operated more than one flight per day.

5.3 Dependent variable

Fare, i.e., the posted price of one seat retrieved by the crawler, represents the dependent variable in the empirical analysis. The fares collected are net of add-ons and other fees, such as charges for the use of credit cards as methods of payment. All fares do not include tax and handling fees. Excluding taxes and fees does not affect our results as the fixed per-passenger tax affects all tickets and thus does not modify the pricing plan based on the flight's capacity. Fares are for a one-way flight and are quoted in Sterling. Focusing only on the outward leg from the UK is not problematic, as it is widely acknowledged that European LCCs charge prices for each leg independently (Bachis and Piga, 2011).

Although from mid-2014 Ryanair started offering a business fare, during the period considered in our analysis the carrier was strictly following an unsegmented pricing strategy, still currently in place for non-business fares, where all tickets carry the same penalties for a name, date and/or route variation: these charges are so high relative to the average price of a ticket that it is often cheaper to buy a new ticket than change it. All tickets permit the same free in-flight hand baggage allowance (max 10 kg) with a fixed fee for each checked baggage (max 15 kg per item). Ryanair started charging a fixed fee for check-in and luggage only in 2006, that is, after our sample period.

5.4 Independent and stratification variables

The independent variables necessary to test our hypotheses relate to the capacity and time dimensions along which the pricing strategy is designed. *AvailableSeats*, which represents the unsold space on a flight on a given booking day, identifies the capacity component of RM. This variable is censored, as its value spans from 1 to 50; additionally, it is endogenous. Its inclusion calls for the implementation of specific econometric refinements, described in the next Section.

The time component of RM is modeled by including a set of dummies corresponding to the different days of booking (*BookingDay*). Additionally, as we know the day in which the booking has taken place, we can control for specific features related to the period of the year during which the query was carried out by including a set of dummies for the month (*MonthOfBooking*) and the day of week (*DayOfWeekOfBooking*) in which the data was retrieved. Finally, some ancillary regressions include other dummy variables for the week number (*WeekNumberOfDept*), the hour (*HourOfDept*) and the route (*Route*) of the scheduled departure.

We stratify the sample based on the hour type (business vs. leisure hours) and the route type (business vs. leisure routes). The first layer is obtained using the scheduled departure date of flights. A flight is operated in *BusinessHours* if its scheduled departure is from 6 a.m. to 10 a.m. and from 6 p.m. to 10 p.m. during weekdays. The remaining flights are operated in *LeisureHours*. The second layer is obtained by using quarterly data on the air traveller flight motivations from the IPS database. More specifically, using IPS data, we compute the city-pair share of business travellers of each flight in our sample. Flights above and below the median (which is 37.1 percent) are respectively denoted as *BusinessRoutes* and *LeisureRoutes*.[3]

Table 1 shows the descriptive statistics as well as the correlation matrix between the dependent variable and other variables of interest for the censored sample, i.e. for *AvailableSeats* < 50. The correlations between the variables are mostly significant and have the expected signs.

5.5 Preliminary results

Tables 2 and 3 show the average value of *Fare*, broken down by route type and, respectively, each of the two RM effects, i.e., available seats and booking days. Because these statistics do not control for important flight characteristics, differences in the mean fare levels across different route and hour types are not particularly informative. However, both Tables provide important insights into the effects of the two RM components (i.e., capacity and time) on fare changes. Table 2 reports the mean *Fare* value across different *AvailableSeats* categories. It describes how the capacity component operates: average prices in each sub-sample tend to increase as the plane fills up. This aspect has been largely neglected in the literature due to the difficulty to match information on a flight's seat inventory with offered fares.

Table 3 reports the mean *Fare* value across different booking days. Two different samples are considered: the whole sample (upper part of the table), and a sub-sample (lower part of the table), containing only the fares from flights with less than 50 seats available. This Table

[3]Note that there is a significant difference among routes. In *LeisureRoutes*, the share of business travellers is 21.3 percent, while in *BusinessRoutes* it is equal to 49.6 percent. IPS data do not consider Ryanair passengers only. Therefore, flights classified as *BusinessRoutes* are those having a large potential number of business passengers for which Ryanair is induced to adjust its RM system. Moreover, traveller motivations are computed on city-pairs and not on routes. Also in this case, it is the presence of business travellers in the city-pair that may induce Ryanair to adjust its RM system.

also confirms the importance of controlling for capacity. Indeed, in the top part, where we do not control for seat capacity, average prices tend to increase constantly as the departure date nears. However, in the bottom part, each row exhibits a U-shaped temporal profile: fares start relatively high, then decrease and then increase in the last 7 to 10 days. Thus, comparing fares without knowing how many seats are left on a plane is likely to lead to biased estimates of the time effect.

The combined evaluation of both Tables is also revealing; the capacity effect operates in a strictly monotonic manner, while the time effect is U-shaped. However, capacity is sold sequentially over time, and so if the temporal effect was only a reflection of the change in remaining seats, then we should also observe a strictly monotonic temporal effect. The fact we do not is suggestive of possible temporal effects that are independent of the evolution of a flight's capacity. Indeed, consistent with Hypothesis 1, in business routes we observe more variability over time, with fares displaying a more pronounced U-shaped behaviour, while in leisure routes the temporal profile seems flatter. Moreover, in accordance to Hypothesis 2, in business hours, fares are more affected by seat availability than in leisure hour.

Because of the simultaneous occurrence of these two effects it is difficult to provide sound conclusions based on descriptive statistics, alone. In the next sections we develop an econometric methodology and we estimate data in order to identify the two effects.

6 Methods

Our aim is to separate fare changes induced by variations in the flight's remaining capacity from time effects that are unrelated to the actual observed evolution of sales. This is important in terms of econometric testing, as we want to investigate how a LCC can use these two dimensions to target different customer segments. Our basic econometric approach consists of estimating the following pricing equation:

$$LnFare = \alpha_0 + \alpha_1\, \mathit{AvailableSeats} + \alpha_2\, \mathit{BookingDay} + \alpha_3\, MonthOfBooking + u, \qquad (1)$$

where the dependent variable, $Fare$, is considered in logs. In equation (1) we include the main independent variables, *AvailableSeats* and the set of *BookingDay* dummies as well as a set of *MonthOfBooking* dummies. The classic ordinary least squares (OLS) model is inappropriate in this context, as *AvailableSeats* has two features which need special attention. First, *AvailableSeats* spans from 1 to 50 and is thus censored, due to the retrieving procedure implemented by the web crawler. This censoring induces a bias in the estimates, and needs to be corrected.

Second, it is endogenous, due to an omitted variable problem: some unobserved determinants of the airline pricing behavior may be correlated with a flight's time-invariant factors. More importantly, the distribution of bucket sizes, which constitutes the pre-set capacity-based pricing plan, may be altered by idiosyncratic, *discretionary* interventions of the airline's revenue manager (Bilotkach et al. 2014).[4]

To deal with endogeneity, we choose two instruments. Their validity depends on the extent they are correlated with the endogenous independent variable, *AvailableSeats*, and uncorrelated with the error term of the pricing equation, u. The first instrument, *BookOnHolidays*, is a dummy variable equals to one if the fare is posted during a holiday period (i.e., main UK Bank Holidays and the week before and after Christmas and Easter). Its effect on *AvailableSeats* may be driven by the fact that the ticket purchasing activity in such periods is likely to be different from non-holiday periods (e.g., when on holiday a person is less willing to spend time planning future trips). Its effect on *AvailableSeats* may be driven by the fact that the ticket purchasing activity in such periods is likely to be different from non-holiday periods (e.g., when on holiday a person is less willing to spend time planning future trips).

The second instrument, *LagMeanSlope*, is the flight-specific and booking day-specific expected slope of the pricing plan. It is constructed as the difference between *TopFare* and *Fare* divided by *AvailableSeats*, using data referring to the same flight identification code and booking date of flights departing on the same day of the week of the three preceding weeks.[5] We choose this lag to capture the fact that pricing plans may change with the day of the week, i.e., the pricing plan for a Monday may be different from the one for a Wednesday. *LagMeanSlope* is expected to increase with occupancy, since the fare plan is convex (see: Table 2). Descriptive statistics for both instrumental variable as well as their correlation with *AvailableSeats* are reported in Table 1.

To handle censoring and endogeneity, we follow the procedure 17.4 in Wooldridge (2002), as applied in Alderighi et al. (2014):

1. We estimate a Tobit specification pooling all observations:
$$AvailableSeats = \beta_0 + \beta_1\, BookingDay + \beta_2\, LagMeanSlope + \gamma\, \mathbf{X} + v, \tag{2}$$

[4]For instance, the manager may *discretionally* decide to expand the size of lower-priced buckets if the flight is not selling as expected; that is, fares may be reduced (increased) when *AvailableSeats* is higher (lower) than expected. The *true* fare setting model should also include the RM analyst's discretionary intervention, *RMI*. As this is unobserved, its effect is included in the error term u; endogeneity is thus due to an omitted variable problem resulting from the correlation between *AvailableSeats* and *RMI*. Therefore, estimation using OLS should produce a downward bias in the coefficient for *AvailableSeats*.

[5]Even if the denominator is censored and equal to 50, this ratio can still be interpreted as the slope of the pricing plan, because *TopFare* represents the value of the 50th seat ahead of the one being sold, whose value is given by *Fare*.

where $\mathbf{X}$ includes week, route, day of booking and time of departure dummies.

2. We retrieve the residuals $\hat{v}$ for the selected sub-sample.

3. On the selected sub-sample, we estimate a modified version of (1), where we include $\hat{v}$ among the regressors to correct for sample selection. As *AvailableSeats* is endogenous, we adopt an Instrumental Variable Two-Stage Fixed Effect (IVFE) estimator, using as instruments *HolidayPeriod* and *LagMeanSlope*.

To estimate (1), given the structure of our data, we focus on a panel where the identifier is the single flight (defined by a combination of departure date and flight code) and the time dimension is given by the time before departure (i.e., the booking day). This panel structure also allows us to control for all unobserved characteristics which are specific to the single flight, such as, for instance, market structure and distance, which do not change during the limited period captured by booking days. Moreover, the fixed-effects approach allows us to control for possible strategic effects at the route level, where, for example, the airline can opt to implement temporary capacity limits, i.e., reduce the number of daily flights.

The choice of instruments is validated by the tests presented in Tables 4-6: the Hansen's J statistic for overidentifying restrictions and the Kleibergen-Paap LM statistic, which tests whether the equation is identified.[6] To anticipate our results, both tests, as well as the weak instruments tests not reported, strongly support our choice of instruments.

7 Results

The econometric procedure from the previous section is applied separately to each sub-sample of flights in, respectively, business vs. leisure routes and business vs. leisure hours, as well as their pairwise combinations. If the estimates reveal that the capacity and the time dimensions play a different role in each sub-sample, we can conclude that the RM at Ryanair was designed to segment its customer basis even if it adopted an unsegmented pricing policy.[7]

[6] The joint null hypothesis of Hansen's J statistic is that the instruments are valid. If the test fails to reject the null hypothesis, then all instruments used are considered exogenous. As for the Kleibergen-Paap LM statistic, a rejection of the null indicates that the matrix of reduced-form coefficients is full column rank and the model is identified.

[7] The estimates from the Tobit and the first stage of the IVFE regressions for the first two hypotheses are reported in the Appendix. It is noteworthy, however, that these estimates are found to be very similar, which suggests that the censoring of *AvailableSeats* induced by the data collection strategy is properly accounted for by the inclusion of the Tobit residuals in the main panel estimation.

The coefficients of *AvailableSeats* in Table 4 (see also: Figure 2) suggest that seat inventory management does not differ significantly between business and leisure routes, although in each sub-sample *AvailableSeats* is an important driver of fares. The negative coefficient implies that, on average, in both sub-samples every time an extra seat is sold the price increases by about 3.0%. Conversely, in line with Hypothesis 1, the evidence points towards sharp differences in the temporal profile of fares: in the last two weeks prior to departure, i.e., during the period when most business travellers learn about their need to travel, fares tend to rise more sharply in business routes, as expected. For instance, all things equal, fares taken one and ten days from departure are, respectively, about 27% $(0.777 - 0.507)$ and 12% $(0.169 - 0.051)$ higher in business routes, relative to the base case of fares posted 21 days prior to departure. Overall, the evidence reported in Table 4 suggests that Hypothesis 1 is supported by the empirical evidence.

In Table 5 (see also: Figure 3), which distinguishes flights according to their departure time and day, the difference between the coefficients of the *BookingDay* dummies is negligible; for instance, after controlling for capacity effects, fares evolve in a similar manner during the two weeks preceding the departure. As Hypothesis 2 predicts, the role of remaining capacity is paramount for flights in business hours; indeed, as revealed by the the coefficients of *AvailableSeats*, such flights tend to have a steeper pricing profile, so that every time a seat is sold, fares on average increase by about 3.6%, as opposed to only 2.9% for flights in leisure hours. In practice, this can be achieved by setting lower fares for the first buckets posted for sale, as also indicated by Table 2: when less than 10 seats remain, the average fare is similar in the two sub-samples of business and leisure hours, but in business hour flights it tends to be lower the more seats remain to sell. Such a profile is consistent with the attempt to smooth demand across flights in leisure and business hours, by inducing leisure travellers to choose flights in business hours.

To test Hypothesis 3, the two previous pairs of sub-samples are further combined to obtain the four sub-samples reported in Table 6. The previous results are robust to this division of the sample: the temporal dimension of RM is important for flights in business routes, while the capacity dimension plays a more crucial role in flights departing during business hours. However, both dimensions are found to be concurrent and significant drivers of fares for flights in business routes and hours. By the same token, a generally flatter temporal and capacity profile characterizes flights in leisure routes and hours. Overall, the results in Tables 4-6 lend support to the view that the adoption of an unsegmented pricing policy does not hinder a firm's ability to organize its RM activities to take advantage of the opportunities that different markets conditions offer.

8 Discussion and conclusions

The literature has clearly identified the characteristics constituting the business model of LCCs, by highlighting, among others, the central role of the Internet as an exclusive distribution channel, the reduced turnaround time made possible by special arrangements with the airports served, the adoption of a single type of aircraft to enhance the specialization of both pilots and aircraft's engineers (Alamari and Fagan, 2005; Bilotkach et al., 2010). However, little attention has been paid to the link between the sustainability of such a business model through the set of pricing strategies generated by the RM. The reason for this may be easily explained by the fact that airlines (whether traditional or low cost) are extremely secretive of their RM approach. Although simpler than the one adopted by FSCs, this study shows that the RM approach by LCCs hinges around a multidimensional set of factors, the level of which can be adjusted according to the characteristics of the markets the airline serves. The outcome is a flexible arrangement where the carrier can differentiate the way it determines the fares it offers to its customers even if officially it is committed to an unsegmented pricing approach. RM allowed Ryanair to tap into the profitable segment of business travellers despite it posted only a single fare at each point in time. The empirical analysis illustrates a firm's ability to implement an adaptive response of its RM system to market conditions that enhanced its ability to extract value from its customers without contravening to the rules imposed by the business model.

The empirical evidence highlights a number of inter-related managerial implications. First, customer segmentation can be pursued even within a business model defined by a standard unsegmented pricing approach where the airline offers a single category of fares. That is, customer segmentation does not require the definition of a menu of multiple simultaneous fares, each with a differing number of included services and restrictions, but may hinge around the exploitation of a segment's known common characteristics, such as, for instance, the tendency of business customers to book late or the high price elasticity of leisure travellers. This is particurarly relevant for Full-Service Carriers, whose traditional segmentation approach might be inappropriate (Teichert et al., 2008). Second, both the capacity and the temporal dimensions of RM are found to be important drivers of fares; therefore, looking at the evolution of fares over time without controlling for the evolution of available seats on a flight is likely to produce biased inferences. Third, and most importantly, the relative role of the two dimensions vary with the market characteristics; they are both paramount in flights operated during business hours in routes with a large potential business travellers' basis, whereas they play a less noticeable role when flights are operated in both leisure times and routes. The overall conclusion is that by fine-tuning its RM approach, an LCC can effectively manage consumer heterogeneity without disrupting its business model based on 'simple, low fares'.

This paper relies on data collected in 2004 and 2005, a period when Ryanair did not offer add-on services. Until mid-2014, Ryanair continued to operate an unsegmented RM approach, although in previous years it had started offering such add-on services as priority boarding, extra luggage, and reserved seats that are generally considered to be valued mostly by business and wealthier leisure travellers. In mid-2014, the carrier introduced a business class, which, in addition to the previous add-on services, also bundles the option of date changes, free airport check-in and fast-tracking through the airport security process. It is still possible for a customer to buy almost every add-on separately, so that three alternative types of tickets are effectively available: 1) 'business' with all bundled services; 2) 'basic standard' plus a range of services a customer is willing to buy separately; and 3) 'basic standard', although only the first and the last are actually shown on the website. It is noteworthy that the business fare is not fixed but effectively moves together with the basic standard fare, the difference between the two being approximately represented by the value of the bundled services when sold separately. Arguably, the 2014 changes, although they facilitated and quickened the online purchase process of the bundled services for some time-constrained customers, do not seem to have fundamentally altered the central role of the RM methods leading to the setting of the basic fare level, to which the business fare is linked. The basic principles highlighted in this study are therefore likely to be applicable even now, i.e., after the carrier has abandoned the unsegmented pricing method.

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TABLES AND FIGURES

Figure 1: Hypothesis 3: RM Strategy combines time and capacity components

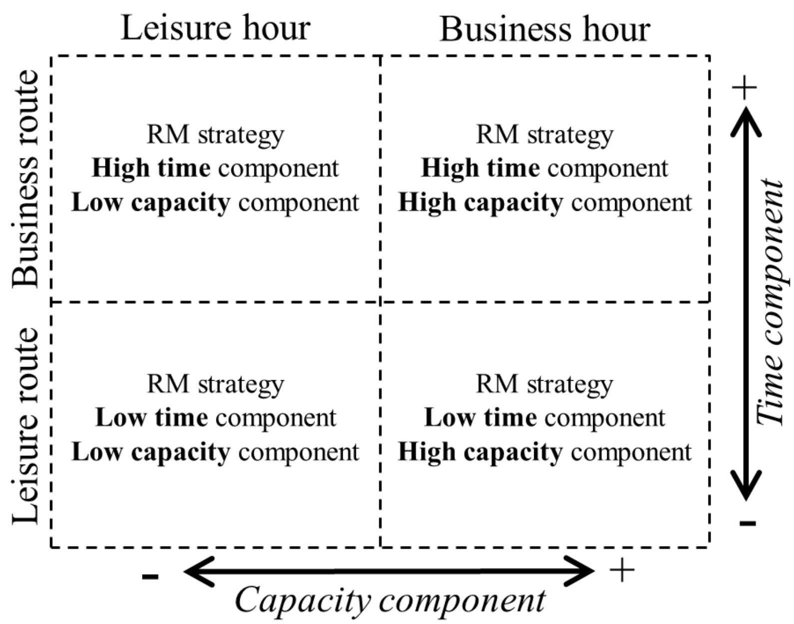

Figure 2: Business and Leisure Routes

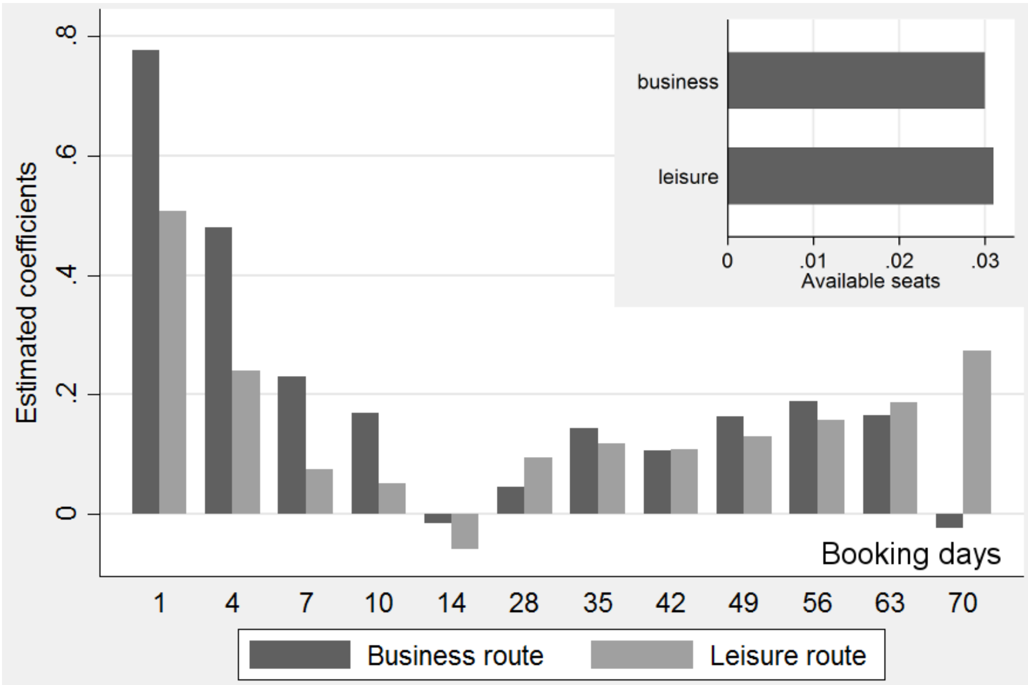

Figure 3: Business and Leisure Hours

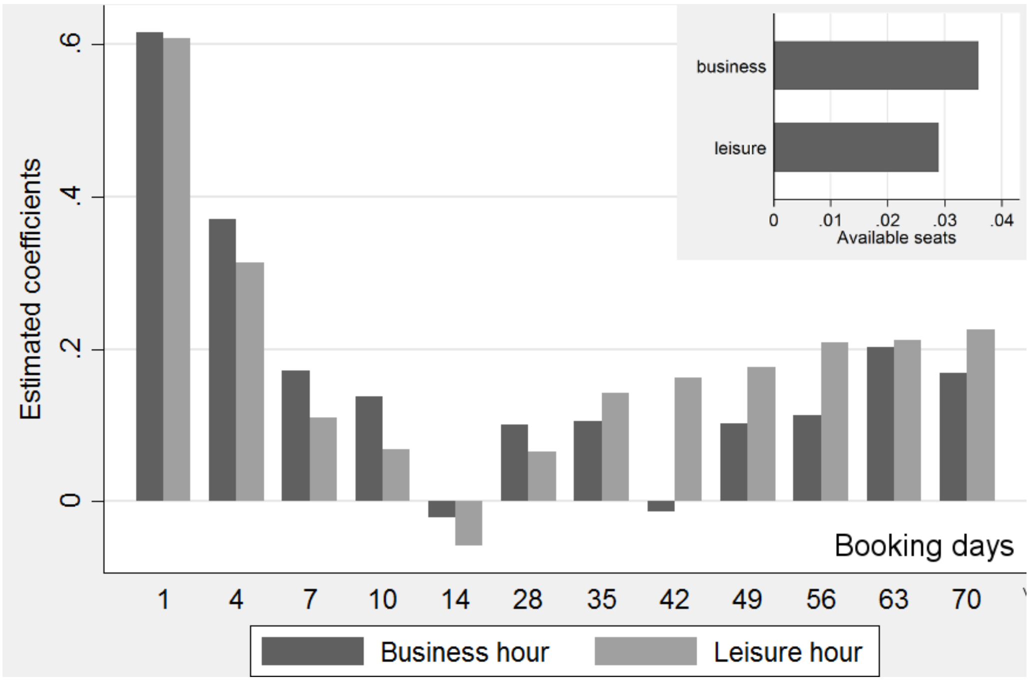

Table 1: Descriptive statistics and correlation matrix

		Mean	S.D.	(1)	(2)	(3)	(4)	(5)	(6)
(1)	Fare	65.57	42.91						
(2)	AvailableSeats	26.21	13.62	-0.60***					
(3)	BookingDay	11.01	11.09	-0.18***	0.33***				
(4)	BusinessRoute	0.48	0.50	-0.12***	-0.02***	-0.09***			
(5)	BusinessHour	0.35	0.48	-0.06***	0.03***	-0.04***	-0.04***		
(6)	BookOnHolidays	0.22	0.42	0.04***	0.02***	-0.01	-0.01**	-0.01**	
(7)	LagMeanSlope	3.05	2.63	0.05***	-0.22***	-0.22***	0.02***	-0.01***	0.000

Note: Statistics computed for Seats<50. Pearson correlations are reported. Significant at *10%, ** 5%, and *** 1%.

Table 2: Descriptive statistics: mean *Fare* by *AvailableSeats* category

		AvailableSeats							
		1-9	10-19	20-29	30-39	40-49	$\geq$50	1-49	Total
Route type	Business	116.7	74.0	53.0	40.5	33.8	16.6	60.1	27.0
	Leisure	123.9	86.5	65.3	52.7	44.6	23.8	70.5	35.8
Hour type	Business	119.4	79.4	56.7	44.7	35.7	16.0	62.3	25.7
	Leisure	121.0	80.8	60.9	48.3	41.9	23.5	67.4	35.5
Route/hour type	Biz/Biz	120.2	74.3	50.3	38.2	31.5	13.7	60.1	22.8
	Lei/Biz	118.6	84.4	61.7	49.2	38.7	18.3	64.4	28.6
	Biz/Lei	114.8	73.9	54.2	41.6	35.0	18.8	60.1	29.9
	Lei/Lei	126.3	87.6	67.5	55.0	48.6	28.2	74.3	41.1

Table 3: Descriptive statistics: mean *Fare* by *BookingDay*

		Booking Day										
All seats		1	4	7	10	14	21	28	35	42	49-70	Total
Route type	Business	81.8	55.0	36.9	31.8	22.5	19.4	17.1	16.2	15.2	14.5	27.0
	Leisure	92.0	63.2	47.6	42.9	33.6	29.6	27.0	25.5	24.4	23.8	35.8
Hour type	Business	79.8	54.6	36.7	32.4	22.5	18.8	16.8	15.5	14.5	13.9	25.7
	Leisure	91.4	61.9	45.9	40.6	32.0	28.9	26.0	25.0	23.8	23.3	35.5
Route/hour type	Biz/Biz	76.3	52.0	33.1	28.1	18.3	15.2	13.3	12.3	11.7	11.1	22.8
	Lei/Biz	83.3	57.2	40.3	36.7	26.6	22.1	20.0	18.5	17.1	16.5	28.6
	Biz/Lei	85.2	56.9	39.4	34.3	25.4	22.5	19.8	18.9	17.7	16.9	29.9
	Lei/Lei	98.3	67.5	52.9	47.3	38.9	35.2	32.2	30.7	29.6	29.1	41.1
		Booking Day										
Seats<50		1	4	7	10	14	21	28	35	42	49-70	Total
Route type	Business	94.2	69.0	53.4	47.1	39.7	39.5	41.8	50.5	55.5	66.6	60.1
	Leisure	101.8	76.1	64.9	60.4	55.4	57.4	61.1	61.7	66.7	77.1	70.5
Hour type	Business	95.1	71.9	56.7	51.0	44.2	44.1	48.5	49.4	52.1	56.0	62.3
	Leisure	99.5	72.9	60.8	55.7	50.3	52.3	55.0	61.1	67.1	80.6	67.4
Route/hour type	Biz/Biz	94.8	71.6	54.3	46.5	38.2	36.9	41.0	48.6	58.5	60.6	60.1
	Lei/Biz	95.4	72.2	58.7	54.7	49.1	49.4	53.2	49.9	49.1	53.1	64.1
	Biz/Lei	93.9	67.8	53.0	47.3	40.6	40.8	42.1	51.3	54.4	69.8	60.1
	Lei/Lei	105.7	78.5	68.7	64.0	59.2	61.8	65.2	66.9	73.5	84.5	74.3

Table 4: Estimates on Business and Leisure Routes

	Route type			
	Business		Leisure	
AvailableSeats	-0.030***	(0.001)	-0.031***	(0.001)
BookingDay1	0.777***	(0.047)	0.507***	(0.036)
BookingDay4	0.479***	(0.040)	0.240***	(0.033)
BookingDay7	0.230***	(0.034)	0.075***	(0.028)
BookingDay10	0.169***	(0.029)	0.051**	(0.023)
BookingDay14	-0.015	(0.024)	-0.059***	(0.019)
BookingDay28	0.046*	(0.025)	0.095***	(0.021)
BookingDay35	0.144***	(0.036)	0.119***	(0.030)
BookingDay42	0.106**	(0.053)	0.108***	(0.042)
BookingDay49	0.163***	(0.060)	0.129***	(0.047)
BookingDay56	0.189**	(0.087)	0.158***	(0.051)
BookingDay63	0.166**	(0.066)	0.186***	(0.058)
BookingDay70	-0.024	(0.108)	0.274***	(0.063)
Tobit residual	-0.000	(0.001)	0.001	(0.001)
DUMMIES:				
MonthOfBooking	YES		YES	
Number of obs.	27,716		30,870	
R2	0.617		0.542	
Excluded instruments:	2		2	
KP LM stat.	$\chi^2(2)$ =258.9***		$\chi^2(2)$=343.3***	
Hansen J stat.	$\chi^2(2)$=0.040		$\chi^2(2)$=0.000	

Note: The dependent variable, $Fare$, is the natural log of the fare obtained from a query for one seat. Bootstrap Standard Errors (SE) are reported in parenthesis, clustered by route and week. 250 repetitions. Significant at *10%, ** 5%, and *** 1%.

Table 5: Estimates on Business and Leisure Hour

	Hour type			
	Business		Leisure	
AvailableSeats	-0.036***	(0.002)	-0.029***	(0.001)
BookingDay1	0.615***	(0.054)	0.608***	(0.036)
BookingDay4	0.371***	(0.048)	0.314***	(0.031)
BookingDay7	0.171***	(0.041)	0.110***	(0.026)
BookingDay10	0.138***	(0.033)	0.069***	(0.021)
BookingDay14	-0.021	(0.028)	-0.058***	(0.016)
BookingDay28	0.100***	(0.032)	0.065***	(0.018)
BookingDay35	0.105**	(0.043)	0.143***	(0.025)
BookingDay42	-0.013	(0.066)	0.163***	(0.035)
BookingDay49	0.102	(0.074)	0.177***	(0.040)
BookingDay56	0.113	(0.093)	0.209***	(0.053)
BookingDay63	0.202**	(0.089)	0.212***	(0.051)
BookingDay70	0.168	(0.115)	0.226***	(0.060)
Tobit residual	0.001	(0.001)	0.000	(0.001)
DUMMIES:				
MonthOfBooking	YES		YES	
Number of obs.	20,397		38,189	
R2	0.593		0.542	
Excluded inst.:	2		2	
KP LM stat.	$\chi^2(2)$ =343.1***		$\chi^2(2)$ =393.5***	
Hansen J stat.	$\chi^2(2)$ =0.098		$\chi^2(2)$ =0.007	

Note: The dependent variable, $Fare$, is the natural log of the fare obtained from a query for one seat. Bootstrap Standard Errors (SE) are reported in parenthesis, clustered by route and week. 250 repetitions. Significant at *10%, ** 5%, and *** 1%.

Table 6: Combining Route and Hour Dimensions

	Route/Hour type							
	Biz/Biz		Lei/Biz		Biz/Lei		Lei/Lei	
AvailableSeats	-0.035***	(0.002)	-0.035***	(0.002)	-0.027***	(0.002)	-0.029***	(0.001)
BookingDay1	0.795***	(0.081)	0.529***	(0.080)	0.794***	(0.053)	0.484***	(0.047)
BookingDay4	0.538***	(0.071)	0.282***	(0.068)	0.471***	(0.046)	0.210***	(0.041)
BookingDay7	0.288***	(0.057)	0.109*	(0.059)	0.216***	(0.040)	0.053	(0.036)
BookingDay10	0.221***	(0.048)	0.094**	(0.048)	0.152***	(0.031)	0.025	(0.029)
BookingDay14	0.020	(0.042)	-0.039	(0.040)	-0.027	(0.027)	-0.066***	(0.024)
BookingDay28	0.078	(0.053)	0.103**	(0.046)	0.020	(0.029)	0.089***	(0.023)
BookingDay35	0.101	(0.070)	0.090	(0.060)	0.139***	(0.039)	0.123***	(0.034)
BookingDay42	-0.085	(0.120)	-0.003	(0.092)	0.143***	(0.055)	0.142***	(0.045)
BookingDay49	0.138	(0.108)	0.050	(0.111)	0.165**	(0.070)	0.148***	(0.055)
BookingDay56	0.183	(0.132)	0.023	(0.134)	0.168	(0.111)	0.180***	(0.060)
BookingDay63	0.164	(0.120)	0.197	(0.136)	0.160**	(0.075)	0.176***	(0.068)
BookingDay70	-0.076	(0.212)	0.289*	(0.169)	0.004	(0.139)	0.256***	(0.068)
Tobit residual	0.001	(0.001)	0.002	(0.002)	-0.001	(0.001)	0.001	(0.001)
DUMMIES:								
MonthOfBooking	YES		YES		YES		YES	
Number of obs.	9,069		11,328		18,647		19,542	
R2	0.644		0.549		0.607		0.549	
Excluded instr.:	2		2		2		2	
KP LM stat.	$\chi^2(2)$ =163.7***		$\chi^2(2)$ =188.8***		$\chi^2(2)$ =165.3***		$\chi^2(2)$ =242.0***	
Hansen J stat.	$\chi^2(2)$=0.344		$\chi^2(2)$=0.000		$\chi^2(2)$=0.000		$\chi^2(2)$=0.023	

Note: The dependent variable, $Fare$, is the natural log of the fare obtained from a query for one seat. Bootstrap Standard Errors (SE) are reported in parenthesis, clustered by route and week. 250 repetitions. Significant at *10%, ** 5%, and *** 1%.

TECHNICAL APPENDIX

Estimates from the Tobit and the first stage of the IVFE regressions for the first two hypotheses are presented in Tables 7 and 8, respectively. These are not meant for publication.

Table 7: Tobit model (dependent variable: *AvailableSeats*)

	Route type				Hour type			
	Business		Leisure		Business		Leisure	
LagMeanSlope	-2.650***	(0.157)	-2.301***	(0.123)	-2.664***	(0.138)	-2.290***	(0.111)
BookingDay1	-31.700***	(0.496)	-29.847***	(0.468)	-34.008***	(0.542)	-30.236***	(0.382)
BookingDay4	-26.009***	(0.494)	-24.966***	(0.463)	-26.993***	(0.526)	-25.998***	(0.389)
BookingDay7	-20.575***	(0.457)	-20.494***	(0.429)	-21.526***	(0.486)	-20.267***	(0.354)
BookingDay10	-15.616***	(0.401)	-15.889***	(0.382)	-17.649***	(0.453)	-16.025***	(0.321)
BookingDay14	-9.676***	(0.341)	-10.238***	(0.319)	-10.361***	(0.358)	-9.851***	(0.269)
BookingDay28	9.299***	(0.381)	9.438***	(0.322)	10.069***	(0.419)	9.059***	(0.280)
BookingDay35	18.532***	(0.583)	16.823***	(0.481)	18.375***	(0.641)	17.236***	(0.416)
BookingDay42	25.211***	(0.747)	23.645***	(0.637)	25.494***	(0.830)	23.839***	(0.537)
BookingDay49	30.104***	(0.985)	28.386***	(0.756)	30.465***	(1.022)	28.602***	(0.685)
BookingDay56	31.194***	(1.236)	30.923***	(0.861)	30.837***	(1.187)	31.261***	(0.786)
BookingDay63	31.514***	(1.362)	31.946***	(0.939)	31.518***	(1.229)	32.041***	(0.899)
BookingDay70	31.915***	(1.542)	34.491***	(1.208)	32.985***	(1.328)	33.699***	(1.059)
Constant	67.691***	(3.624)	78.259***	(3.299)	70.047***	(9.629)	65.036***	(2.896)
DUMMIES:								
DayOfWeekOfBooking	YES		YES		YES		YES	
WeekNumberOfDept	YES		YES		YES		YES	
HourOfDept	YES		YES		YES		YES	
Route	YES		YES		YES		YES	
Number of obs.	146,267		147,854		119,775		174,346	
Pseudo R2	0.178		0.175		0.184		0.170	

Note: Standard errors clustered by route and week. Significant at *10%, ** 5%, and *** 1%.

Table 8: First stage (dependent variable: *AvailableSeats*)

	Route type				Hour type			
	Business		Leisure		Business		Leisure	
HolidayPeriod	0.386***	(0.085)	0.109***	(0.029)	0.287***	(0.069)	0.155***	
LagMeanSlope	-2.320***	(0.016)	-2.212***	(0.007)	-2.364***	(0.019)	-2.164***	(0.001)
BookingDay1	-30.973***	(0.111)	-29.413***	(0.040)	-31.272***	(0.100)	-29.855***	(0.047)
BookingDay4	-24.924***	(0.114)	-24.516***	(0.044)	-25.739***	(0.106)	-24.666***	(0.041)
BookingDay7	-19.836***	(0.096)	-20.158***	(0.034)	-20.605***	(0.088)	-19.895***	(0.036)
BookingDay10	-14.372***	(0.107)	-15.463***	(0.040)	-15.595***	(0.099)	-14.952***	(0.029)
BookingDay14	-9.163***	(0.070)	-10.025***	(0.024)	-9.703***	(0.064)	-9.588***	(0.024)
BookingDay28	8.442***	(0.085)	9.182***	(0.027)	9.156***	(0.080)	8.719***	(0.023)
BookingDay35	16.392***	(0.138)	16.404***	(0.040)	16.465***	(0.116)	16.568***	(0.034)
BookingDay42	22.188***	(0.175)	23.001***	(0.053)	22.854***	(0.159)	22.787***	(0.045)
BookingDay49	26.091***	(0.271)	27.560***	(0.066)	27.260***	(0.220)	27.229***	(0.055)
BookingDay56	27.272***	(0.300)	29.999***	(0.083)	27.394***	(0.302)	29.854***	(0.060)
BookingDay63	27.571***	(0.489)	30.895***	(0.112)	28.009***	(0.426)	30.554***	(0.068)
BookingDay70	27.711***	(0.437)	33.309***	(0.119)	29.183***	(0.409)	32.046***	(0.068)
Tobit residual	0.838***	(0.005)	0.955***	(0.002)	0.860***	(0.004)	0.931***	(0.001)
DUMMIES:								
MonthOfBooking	YES		YES		YES		YES	
Number of obs.	27,716		30,870		20,397		38,189	
R2	0.948		0.984		0.952		0.976	

Note: Standard errors clustered by route and week. Significant at *10%, ** 5%, and *** 1%.