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Multi-dimensional price elasticity for leisure and business destinations in the low-cost air transport market: evidence from easyJet

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Abstract

This study investigates the price elasticity of demand in the European low-cost carrier (LCC) industry by analysing Internet fares for all easyJet flights departing from the Amsterdam Schiphol airport towards 21 European destinations between March and September 2015. Results suggest that the price elasticity of demand greatly varies across different dimensions, ranging from -0.535 for the business-oriented route of Hamburg to -1.915 for the leisure-oriented route of Split. Price elasticity is also found to be higher for reservations made more days in advance, for reservations and departures occurring on weekends, and for flights taking off during lunchtime and in the summer period. All results are consistent with the different behaviours of leisure and business passengers and the ongoing increase in the business component of the LCC passenger mix.

Keywords: LCCs; leisure index; seasonality; easyJet

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Highlights

- This article analyses price elasticity of demand for leisure and business destinations
- easyJet's price elasticity of flights departing from the AMS airport is overall inelastic
- During the summer, price elasticity of demand on average increases
- Price elasticity is higher for weekends-reservations and -departures and lunchtime flights
- Price elasticity is higher for reservations made more days in advance

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Introduction

In the current arena, low-cost carriers (LCCs) have been required to continuously adjust their ticket prices in response to rapid changes in market conditions (Alderighi et al., 2015). In this regard, reducing costs in the short term, forecasting demand, and understanding demand changes according to price variations have increasingly become crucial prerequisites underpinning LCCs' success (e.g. Alderighi et al., 2015; Malighetti et al., 2009; Narangajavana et al., 2014). Furthermore, the fact that LCCs have begun to rely on the business component, i.e. through the hybridization process[1] (Klophaus et al., 2012, Morandi et al., 2015), makes it even more interesting to understand the price elasticity dynamics in this sector. Indeed, on the one hand, the low-cost strategy has been well recognised since its establishment to target passengers who are highly sensitive to price changes (leisure component), whereas on the other hand, this ongoing hybridization process mixes the types of passengers by targeting the most inelastic ones (business component).

Historically, LCCs have not implemented third-degree price discrimination by providing different travel classes, and instead, they have generally relied on intertemporal price discrimination to suit passengers' various willingness to pay (Moreno-Izquierdo et al., 2015). However, the recent orientation towards the business component makes it more crucial to understand different LCC passengers' price elasticities. In this study, we aim to shed light on LCC passengers' price sensitivities by investigating how the price sensitivity changes across all of the different facets that characterise the air transport service, from the route and seasonal dimensions to the most traditional dimensions explored in the previous literature in other contexts, such as variations in flight and booking characteristics (Mumbower et al., 2014).

Notwithstanding the importance of identifying demand changes in relation to price variations, the estimation of price elasticity is largely missing in the literature, mainly due to the lack of available data on both prices and the number of booking passengers (Brons et al., 2002). To date, the difficulty of collecting data has made it challenging to acquire an in-depth exploration of price elasticity, preventing an overall comprehension of its dynamics. This lack of data has made it difficult to go beyond the average value of price elasticity and understand the dimensions across which it varies (Oum et al., 1992). The few existing contributions in this regard are limited to analysis of the price elasticity of demand in the American context (Brons et al., 2002, Granados et al., 2012a; Granados et al., 2012b; Mumbower et al., 2014) and mainly

[1] LCCs have increasingly begun to adopt some features of full-service network airlines (e.g. offering more than one class of service, providing meals and other in-flight services, starting hubbing activities, and shifting to primary airports).

focus on the pricing strategies of traditional carriers. Only Mumbower et al. (2014) provide an analysis of the pricing strategies of a US low-cost carrier (JetBlue) on solely four routes.

In order to investigate the price elasticity of demand in the European LCC air transport industry, we examine Internet fares for all flights on easyJet (the second European LCC in terms of passengers in the year 2015[2]) that depart from the Amsterdam Schiphol airport towards 21 European routes between March and September 2015. The peculiarities of the European context, such as the geographic extension of the market, the development of the hub-and-spoke model, and the number of inter-modal alternatives (Brons et al., 2002; Giaume & Guillou, 2004; Moreno-Izquierdo et al., 2015), allow us to draw new insights that complement the existing US-based evidence on passengers' price sensitivities of demand (Granados et al., 2012b). Consistent with the former literature, we implement an instrumental variable approach to correct for price endogeneity so as to provide unbiased estimates of the price elasticity of demand across the different dimensions.

The remainder of this paper is organised as follows. Section 2 reviews the state of the art studies of the price elasticity of demand. Section 3 describes the research design and methodology. Section 4 reports the results of the preliminary and empirical analyses. Section 5 summarises the conclusions and proposes directions for further research.

1. Literature review

Airlines' pricing strategies have been a topic of relevant interest over time. Research scholars have attempted to understand the dynamics of fare setting, which were found to depend on factors such as advance booking (e.g. Bergantino & Capozza, 2015; Dana, 1999), the degree of market concentration (e.g. Giaume & Guillou, 2004; Malighetti et al., 2010; Malighetti et al., 2015; Stavins, 2001), the demand level (e.g. Alderighi et al., 2015; Escobari, 2012), the reservation characteristics (e.g. Cattaneo et al., 2016; Mantin & Koo, 2010), or even the types of consumers (Li et al., 2014) or the routes (Salanti et al., 2012). However, the understanding of the price elasticity of demand has largely remained unexplored in the air transportation literature (Bijmolt et al., 2005), especially when considering the extent to which it varies across different dimensions, such as the routes' and passengers' characteristics (Granados et al., 2012b). Since the 1990s, scholars have suggested that the price elasticity might vary according

[2] This finding comes from The European Low Fares Airline Association (June 2015).

to the nature of the travel (Brons et al., 2002; Oum et al., 1992) and the presence of substitute modes (Brons et al., 2002).

Based on the few existing empirical studies dealing with the price elasticity of demand, the elasticity is indeed found to vary according to the different dimensions considered. On average, investigating economy class reservations made through the global distribution system across 47 city pairs during the period September 2003–August 2004, Granados et al. (2012a) find a price elasticity of demand of -1.03. They show, however, that the price elasticity varies across different sale channels (online vs. traditional) and different market segments (business vs. leisure). Their results highlight that the elasticity is higher for leisure passengers who reserve tickets online compared to business travellers who book through traditional channels. Specifically, they find an offline (online) elasticity ranging from -0.34 (-0.89) for business passengers to -1.33 (-1.56) for leisure travellers. Granados et al. (2012b) conduct a similar study focusing on the booking records of a large traditional airline for the periods of February–March 2009 and February–April 2010 across 40 city pairs. They point out that passengers are always non-price sensitive (average value of -0.64) but still highlight that, on average, leisure travellers are more price elastic. The only previous study focusing on LCCs (Mumbower et al., 2014) shows that, although passengers are price elastic overall (-1.97 at the mean price), the demand is still inelastic for reservations made one to two days before departure. Interestingly, elasticity values are often greater than unity at different levels of the same dimension, thus changing the dynamics of demand variations in price changes.

This study therefore aims to contribute to the former literature by investigating price elasticity in the European LCC industry, adding to the past contributions on the exploration of price elasticity variation across the route and seasonal dimensions. The importance of this analysis lies in the existing differences between the European and US air transportation markets. On the one hand, routes are on average shorter in Europe, thus implying more competition from alternative transport modes and more moderate use of airports as hubs (Brons et al., 2002; Giaume & Guillou, 2004). On the other hand, Europe is characterised by more seasonal airline demand than is the US because of both its geographic structure and the role that LCCs have played over time. In particular, compared to the US, a large part of Europe (e.g. the Southern countries) has been characterised by the typical high seasonality of tourists during the summer (Garrigos-Simon et al., 2010; Graham & Dennis, 2010; Papatheodorou, 2002). In addition, the European LCCs' schedules have partially integrated the traditional periodicity of charter flights after a decline in the frequency of the latter (Martinez-Garcia & Royo-Vela, 2010; Williams, 2001).

3. Research Design

3.1. Sample and data

In order to measure the price elasticity of demand across different dimensions, we first implement a linear regression model analysing the factors that influence the number of tickets sold, which represents our proxy for demand (Granados et al., 2012b). For this purpose, we develop a unique dataset including all daily web fares for easyJet flights on 21 European routes[3] (Figure 1) departing from the Amsterdam Schiphol airport during the period 8 March–23 September 2015 for bookings made 1–45 days before departure. Overall, the data includes daily web fares for 7,211 scheduled flights.

There are several reasons to consider easyJet for a multi-dimensional analysis of the price elasticity of demand. Anticipating the strategy of Ryanair, its major competitor, easyJet began to target passengers with a higher propensity to fly, i.e. business passengers, by establishing in primary airports and serving primary routes (easyJet Annual Report, 2016). Indeed, in 2015, easyJet tried to increase its European market share by both reinforcing its strong position in already served airports, like London Gatwick and Milan Malpensa, and opening important new bases, like Amsterdam Schiphol airport[4] (easyJet Annual Report, 2016). This airport, the fourth largest European airport in terms of offered seats in 2015 (OAG, 2015), creates major opportunities for the low-cost carrier as it is located in one of the most important European capital cities and is of great interest to both leisure and business travellers. According to easyJet (easyJet Annual Report, 2016), the combination of using primary airports and offering highly frequent and attractively timed flights helps the company to serve not only leisure passengers, who would choose a low-cost carrier, but also business consumers, who represent a high source of revenue for the company. To better fulfil this purpose, easyJet offers different fares across different distribution channels, selling flight tickets directly from its own website and even through online travel agencies and GDS systems (easyJet Annual Report, 2016). Hence, the choice to focus the empirical analysis on the easyJet-Amsterdam pair also

[3] The 21 European destinations are as follows: Split (SPU) in Croatia; Prague (PRG) in the Czech Republic; Bordeaux (BOD) in France; Hamburg (HAM) and Berlin (SXF) in Germany; Rome (FCO) and Milan (MXP) in Italy; Lisbon (LIS) in Portugal; Basel (BSL) and Genève (GVA) in Switzerland; and Belfast (BFS), Bristol (BRS), Edinburgh (EDI), Glasgow (GLA), London (LGW, LTN, and STN), Liverpool (LPL), Manchester (MAN), Newcastle (NCL), and Southend (SEN) in the United Kingdom.

[4] easyJet is the major low-cost carrier operating at the AMS airport, where it does not suffer from the presence of its major competitor, Ryanair.

allows us to identify the different price elasticities of demand for business and leisure passengers.

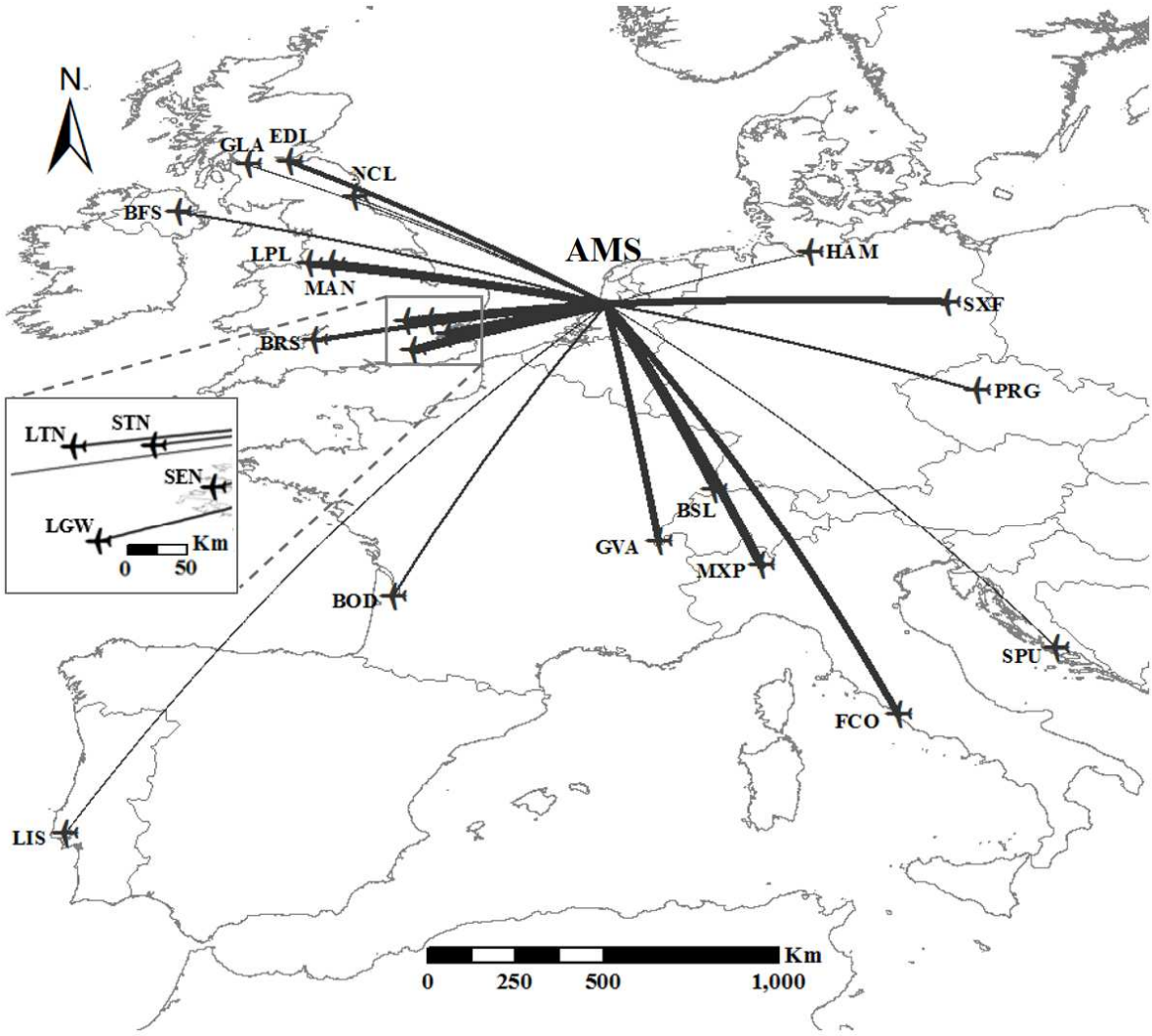

Figure 1. easyJet's routes during the period March–September 2015

Note: The thickness of the flows represents the intensity of the flights offered by easyJet on that route

3.2. Methodology and variables' definitions

When investigating the relationship between price and demand, the problem of reverse causality may arise, since the level of demand is clearly affected by the price. Consistent with recent studies analysing air transport pricing strategies (Granados et al., 2012b; Mumbower et al., 2014), we attempt to solve price endogeneity by considering a two-stage least squares instrumental variable method with robust standard errors, where the selected instrumental variable is correlated with the price but is not included in the demand equation. Similar to

Mumbower et al. (2014), the airline's average prices in all other markets with a similar length of haul are used as an instrumental variable (Gayle, 2004; Hausman, 1996)[5]. Specifically, we first aggregate routes according to the distance between the origin and the destination, creating three classes: between 300 km and 550 km, between 551 km and 800 km, and more than 800 km. Second, for each route *m,* we compute the average price on routes *n-m* that are in the same class as route *m*. The validity of this instrument lies in the satisfaction of two diagnostic tests. The Hansen *J* test highlights that the instrument is correlated with the endogenous variable (the price) and thus shows that the equation is exactly identified, and the Kleibergen-Paap Wald statistic indicates that the instrument is not weak (the value is 128.460).

The two stages of the model are as follows:

Stage 1:

$$P_{irdt} = \alpha + \beta IV_{rdt} + \gamma X_{irdt} + \varepsilon_{irdt} \qquad (1)$$

Stage 2:

$$D_{irdt} = \delta + \theta \widehat{P_{irdt}} + \vartheta X_{irdt} + u_{irdt} \qquad (2)$$

In the first stage, P_{irdt} is the price for a seat purchased by a single passenger *t* days in advance for flight *i* on route *r* departing on day *d;* IV_{rdt} is the instrumental variable defined as the airline's average prices in all other markets with a similar length of haul; and ε_{irdt} is the error term. In the second stage, D_{irdt} is the number of tickets sold at time *t* on route *i*, and $\widehat{P_{irdt}}$ is the predicted price from the first stage. Similar to the first stage, u_{irdt} is the error term. In both stages, X_{irdt} is a vector that represents a set of explanatory variables. Specifically, it is composed of:

- Four dummy variables identifying the hour of departure: from 7 a.m. to 9.59 a.m. (*Morning*); from 10 a.m. to 1.59 p.m. (*Lunchtime*); from 2 p.m. to 5.59 p.m. (*Afternoon*); and from 6 p.m. to 9.59 p.m. (*Evening*), which represents the reference case.
- Two sets of dummy variables for the departure and booking days consisting of one dummy variable for each day of the week (*Saturday* represents the reference case).

[5] As highlighted by the recent literature, in air transportation economics, different types of instrument variables can be implemented to solve the potential endogeneity issue. However, testing the validity of different instruments is out of the scope of this study (see Mumbower et al., 2014 for a complete picture of different instruments).

- The variables *LC Dominance* and *Eligible Alternatives*, which account for direct and inter-modal competition and thus help to avoid under-estimated results (Oum et al., 1992). The former is easyJet's market share on that route compared to those of the other low-cost carriers[6], and the latter represents the presence of eligible alternatives, considering both different transport modes and alternative airports at the destination, on each of the 21 routes from the Amsterdam Schiphol airport. An eligible alternative is identified by considering both the cost and the time dimensions. In particular, we first multiply the time required for each alternative (t_a) by its average price (C_a), computed to be between the minimum and the maximum offered by the Rome2rio.com website, a platform that provides information about different transport modes for each origin-destination pair. Second, we consider as eligible alternatives only those options where either the time or the cost (or both) are lower than the air route option and where the absolute value of the product of time and cost is not greater than 20% of the reference case. Specifically, we use the formula:

$$\left|1 - \frac{(C_a * t_a)}{(C_r * t_r)}\right| < 0.20 \qquad (3)$$

  where C_a (t_a) and C_r (t_r) are the average costs (times) of the alternative and the reference case, respectively.
- A set of six dummy variables representing the months of departure, where *September* is the reference case.
- The number of days in advance (1 to 45) at which a ticket is bought (*Advance*).
- A set of 21 dummies identifying each of the 21 European destinations considered, where *SXF* (Berlin) represents the reference case.

After the first stage of the analysis, we move forward to understanding the dynamics of the price elasticity of demand across different dimensions, which is an essential analysis to wholly comprehend the relationship between price and demand (Granados et al., 2012b).

Specifically, we estimate the price elasticity of demand at mean values across each dimension starting from the common definition of elasticity (Schiff and Becken, 2011):

$$\eta_{D,\hat{P}} = \frac{\partial D}{\partial \hat{P}} \cdot \frac{\hat{P}}{D} = \theta \cdot \frac{\hat{P}}{D} \qquad (4)$$

[6] The other low-cost carriers we consider are Vueling, Germanwings, Transavia, and Flybe, operating on the Rome-Fiumicino, Hamburg, Lisbon, and Manchester routes, respectively.

where $\widehat{P}$ and D represent the predicted price and the demand, respectively, and θ is the price coefficient of second stage in the two-stage least squares regression model (See Equation 2). Considering the elasticity at the means, $\eta_{D,\hat{P}}$ becomes:

$$\eta_{D,\hat{P}} = \theta \cdot \frac{\bar{\hat{P}}}{\widetilde{D}} \qquad (5)$$

where $\bar{\hat{P}}$ is the overall average of the predicted prices and $\widetilde{D}$ is the predicted value of demand computed as in Equation 2, where all of the independent variables are equal to their own averages. To evaluate the variation in $\eta_{D,\hat{P}}$ over a subcategory k (e.g. *Morning, Lunchtime, Afternoon,* and *Evening)* of a specific dimension K (e.g. *Departure Hour*), Equation 4 becomes:

$$\eta_{D_k,\widehat{P_k}} = \theta \cdot \frac{\overline{\widehat{P_k}}}{\widetilde{D_k}}, \text{ with } k \in K \quad (6)$$

where $\overline{\widehat{P_k}}$ and $\widetilde{D_k}$ are the average predicted price and the predicted value of the demand, respectively, estimated for each subcategory k of the dimension K.

Consistent with previous studies, we provide evidence of how the price elasticity of demand varies with respect to advance booking and the reservation day (*booking dimension*) and according to the different days and hours of departure (*flight dimension*). After this preliminary investigation, we go into more detail exploring the *route* and the *seasonal dimensions* by investigating how price elasticity varies for different destinations and seasons (spring and summer) of departure.

We collect data on unit fares and tickets sold directly from easyJet's website, whereas the identification of other carriers operating on each route and the eligible alternatives are made using the Amsterdam Schiphol website and Rome2rio.com, respectively. Specifically, to determine the number of tickets sold, we checked the maximum bookable seats daily for each flight, up to easyJet's website threshold of 40 seats, and the difference between this value on day *t* and on day *t+1* represents the number of tickets bought each day[7].

3.3. Descriptive statistics

On average, the number of tickets sold is 2.4 per day, with a maximum of 39 tickets sold to Fiumicino, Rome, departing on 23 June 2015 (price: 59.99 €). In addition, 33 tickets to Malpensa, Milan were sold on 5 August 2015 (price: 85.99 €). After the destinations in Italy,

[7] In detail, we first checked if 40 seats were available. If yes, we checked for lower numbers of seats that were multiples of 5. When the flight was sold out for a specific quantity n (a multiple of 5), we controlled for the fare offered for $n-1$ seats up to the number of seats for which the price was available. The ultimate number of seats for which the price was available thus represents the number of available seats on that day. The difference between this value and the same value calculated the day before represents our proxy for demand, as in Granados et al. (2012b).

Prague is found to have the highest number of tickets sold in a day, with 28 tickets sold on 7 May 2015 (price: 117.99 €). Overall, zero tickets per day were sold in 28.7% of the cases.

The average price for easyJet's flights departing from the Amsterdam Schiphol airport during the period 8 March–23 September, 2015 is 117.47 €. The lowest price is 29.99 € for the destination of Belfast on 31 March 2015, and the highest price is for the flight to Berlin on 5 June 2015 (461.99 €). On average, for flights departing during the spring, the price is 112.38 €, and this average increases 11% (124.60 €) during the summer.

The routes in our sample show easyJet as the main LCC, with an average low-cost market share of 92%. This high value is due to easyJet's monopoly in the low-cost market on 17 of the 21 routes. The Lisbon route, for which easyJet offers three flights per week, has the minimum *LC Dominance* value of 33%, whereas for the other three routes where easyJet does not have a monopoly, Rome-Fiumicino, Hamburg, and Manchester, the low-cost dominance variable has a value of around 50%.

Considering the number of eligible alternatives to easyJet for each route, five routes (out of 21) are attainable by choosing other flights landing in a different airport than that used by easyJet. Up to six routes are served by bus from the Amsterdam Schiphol airport, and two UK destinations (London-Luton and London-Stansted) are also reachable by ferryboat. Four destinations (London-Gatwick, London-Luton, London-Stansted, and Berlin) are reachable by rail. Overall, British destinations are well served from the Amsterdam Schiphol airport.

4. Results

4.1. Preliminary results

First, we analyse the price and demand over time. As shown in Figure 2, the average fare increases over time, from a minimum of 82.78 € to a maximum of 124.80 € on the 21st and on the last day in advance, respectively. This result corroborates the usual intertemporal price discrimination strategy for LCCs, where higher airfares are offered as the departure day approaches (e.g. Alderighi et al., 2015; Bergantino & Capozza, 2015; Stokey, 1979). Interestingly, the average demand shows an increasing trend from a minimum of 1.10 passengers booking on the 21st day of advance to a maximum of 3.07 passengers booking a week before departure. Computing the ratio between the average daily variation in fares and demand results in a steadily decreasing pattern until the 12th day in advance, after which the ratio begins to increase. The ratio ranges from 1.81 on the 17th day in advance to -0.47 on the 12th day in advance. Overall, this trend has a ratio of around 1.4, implying that passengers continue to buy tickets, neglecting the increase in prices. This result suggests that passengers

booking in the last 10 days prior to departure are not as price sensitive as travellers reserving their seats further in advance, which corroborates the argument that tickets sold close to the departure date are often bought by business passengers, who are known to be price-inelastic consumers (e.g. Bergantino & Capozza, 2015; Dana, 1999; Salanti et al., 2012).

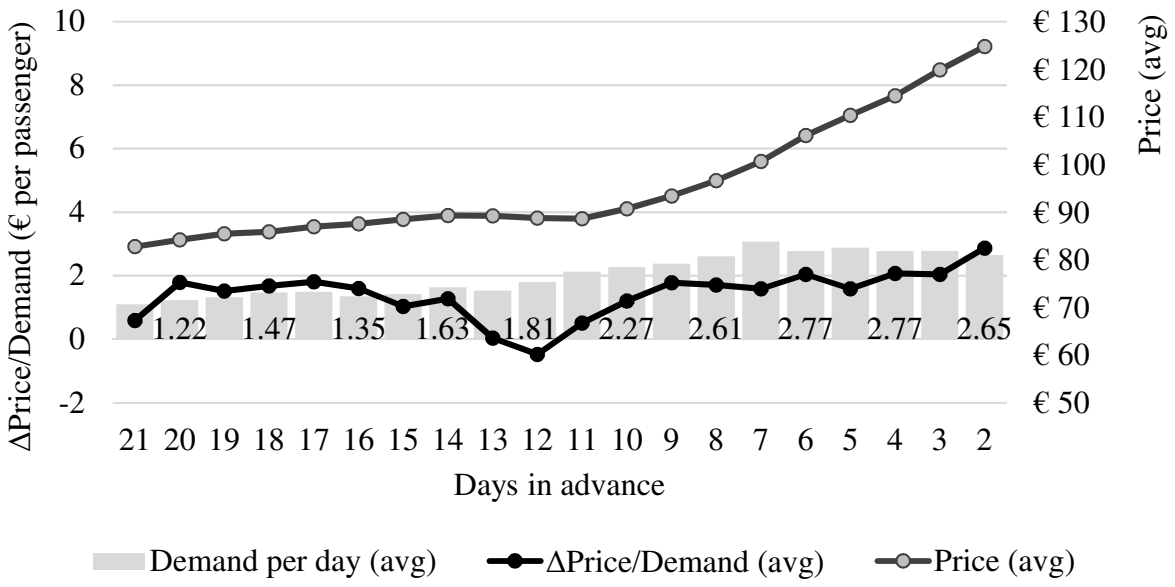

Figure 2. Demand and price values by number of days in advance

4.2. Empirical results

Table 1 reports the results of the ordinary least squares (OLS) and the two-stage least squares (2SLS) instrumental variable regressions. As expected, in both models, demand is negatively and significantly related to the offered price, suggesting that the lower the price, the higher the number of passengers booking a ticket. Interestingly, when the value of easyJet's market share decreases or the number of eligible alternatives increases, demand decreases. This finding seems reasonable since the greater the number of alternative modes to reach a destination, the greater the price sensitivity of the travellers (Brons et al., 2002).

The results for the two models are very similar, with a higher price coefficient (negative) in the 2SLS model than in the OLS model[8]. This evidence is consistent with the previous literature (e.g. Guevara & Ben-Akiva, 2006; Mumbower et al., 2014).

[8] Multicollinearity tests dismissed the potential for problems since none of the mean variance inflation factors exceeded the typical cut-off of 10.

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315 **Table 1 – OLS and 2SLS regression estimates on demand**

	OLS		2SLS[a]	
	Coefficient	**Robust St. Error**	**Coefficient**	**Robust St. Error**
Price	-0.011***	0.000	-0.015***	0.004
Eligible Alternatives	-0.053***	0.012	-0.056***	0.012
LC Dominance	0.799***	0.130	0.722***	0.154
Departure Hours (Evening is the ref. case)				
Morning	-0.011	0.027	-0.065	0.064
Lunchtime	-0.210***	0.032	-0.251***	0.054
Afternoon	-0.059**	0.029	-0.073**	0.032
Departure Days (Saturday is the ref. case)				
Sunday	0.282***	0.032	0.407***	0.138
Monday	0.545***	0.033	0.562***	0.039
Tuesday	0.861***	0.041	0.825***	0.055
Wednesday	0.851***	0.041	0.810***	0.059
Thursday	0.906***	0.038	0.906***	0.038
Friday	0.600***	0.033	0.609***	0.035
Reservation Days (Saturday is the ref. case)				
Sunday	0.146***	0.027	0.141***	0.028
Monday	1.541***	0.032	1.535***	0.033
Tuesday	1.499***	0.032	1.492***	0.033
Wednesday	1.501***	0.033	1.492***	0.034
Thursday	1.403***	0.033	1.395***	0.034
Friday	1.243***	0.032	1.241***	0.032
Month (September is the ref. case)				
March	-0.451***	0.041	-0.539***	0.103
April	-0.383***	0.038	-0.386***	0.038
May	-0.411***	0.039	-0.436***	0.047
June	-0.179***	0.040	-0.222***	0.061
July	0.122***	0.041	0.173**	0.069
August	-0.331***	0.040	-0.332***	0.04
Advance	-0.064***	0.001	-0.064***	0.002
Constant	2.704***	0.110	3.273***	0.619
Observations	66,716		66,716	
Adjusted R-squared	0.177		-	
F-statistic	311.39		264.35	

[a]Endogeneity diagnostic tests:
Weak identification test Kleibergen-Paap rk Wald F statistic: 128.460
Hansen J statistic overidentification test of all instruments: Equation exactly identified

316 *Notes: *** ,**, and * indicate statistical significance at the 1%, 5%, and 10% levels,*
317 *respectively. Destination dummies are included in both models*

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After estimating using the two-stage least squares instrumental variable method, we compute the price elasticity of demand. Our results suggest that the elasticity at the mean price is below unity and is equal to -0.753, thus indicating that a 1% increase in the price generates a 0.8% decrease in the demand for air travel. Our findings highlight that in the case of a European low-cost vector, easyJet, the price elasticity of demand is rigid during the period of March–September 2015. Although LCCs are expected to face a more elastic demand (e.g. Mumbower et al. (2014) find an elasticity of -1.97 in the case of JetBlue,), we argue that the value below unity is for two reasons. First, easyJet more directly targets business passengers as compared to other LCCs by offering flexible fares and operating in primary airports (e.g. Mason, 2000; Papatheodorou & Lei, 2006). Second, the Amsterdam Schiphol airport is recognised to be an important hub for business affairs.

Disentangling the mean value of the price elasticity across different dimensions (booking, flight, route, and season), we are able to better understand how demand changes as price changes under different conditions. Further, to better explore this phenomenon, we investigate variations across the booking, flight, and route dimensions when considering different seasons (spring and summer).

4.2.1. Booking dimension

We first observe how the price elasticity of demand varies according to the number of days in advance that the ticket is booked. Figure 3 depicts the elasticity values. As the departure date approaches, the price elasticity of demand ranges from -2.066 to a minimum of -0.638 four days before departure. Air travel demand dynamically changes from being elastic to being rigid between the 14th and 13th days before departure. This particular elasticity pace can be explained by considering that leisure and business passengers are likely to respond differently to price changes (Brons et al., 2002; Oum et al., 1992). It is indeed well known that business passengers are less price sensitive than leisure passengers (Alderighi et al., 2016; Granados et al., 2012a; Granados et al., 2012b) and that they are used to buying flight tickets only a few days before departure (Alderighi et al., 2016; Salanti et al., 2012). The increase in the proportion of business passengers over time is therefore one of the factors responsible for the decrease in the elasticity. This result is analogous to that of Mumbower et al. (2014): the elasticity increases as the departure day moves further away.

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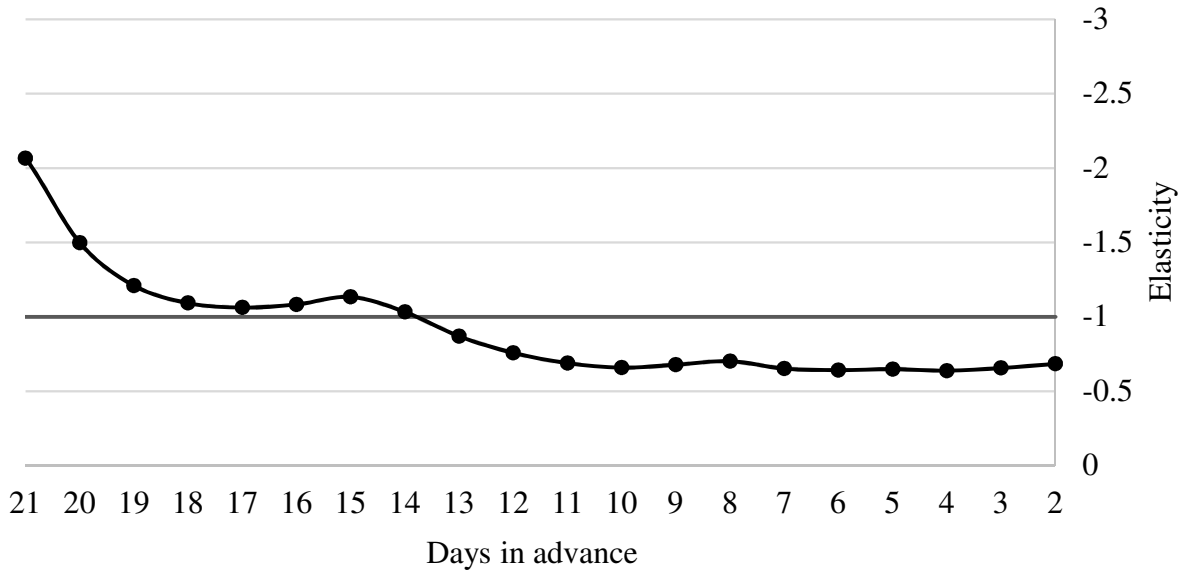

Figure 3. Price elasticity values by days in advance

Notes: All elasticity values are significant at the <1% level
The ANOVA F-statistic (43) is 26.76, significant at the <1% level

Table 2 – Price elasticity values per booking day

Elasticities over the Booking Dimension	
Booking Day	
Working Days	-0.651
Monday	-0.613
Tuesday	-0.635
Wednesday	-0.641
Thursday	-0.666
Friday	-0.710
Weekends	-1.226
Saturday	-1.303
Sunday	-1.154
ANOVA F-statistic (6)	126.59***

Notes: All elasticity values are significant at the <1% level
**** indicates statistical significance at the 1% level*

Similarly, we compute price elasticity changes according to the booking day of the week. As shown in Table 2, although it is below unity, the elasticity increases gradually from Mondays (-0.613) to Fridays (-0.710), whereas during weekends, passengers are significantly more price sensitive (the price elasticity of demand is -1.303 and -1.154 on Saturdays and Sundays, respectively). This result corroborates the argument that business passengers, who are known

to generally be less price sensitive, usually buy tickets during weekdays (Mantin & Koo, 2010), whereas leisure travellers, who are more price sensitive and have lower search costs, book their flights on the weekends (Mumbower et al., 2014).

4.2.2. Flight dimension

The price elasticity is also found to vary according to the departure day. As shown in Table 3, passengers seem to be price insensitive on weekdays, and they become more price sensitive on weekends, especially on Sundays (-1.131). This finding suggests that leisure passengers typically travel on weekends, whereas business travellers are more used to travelling on working days. The day of the week therefore represents one of the drivers used by LCCs to differentiate between business and leisure passengers and to suit their various willingness to pay (Salanti et al. 2012).

Table 3 – Price elasticity values per departure day and departure hour

Elasticities over the Flight Dimension	
Departure Day	
Working Days	-0.642
Monday	-0.737
Tuesday	-0.553
Wednesday	-0.585
Thursday	-0.587
Friday	-0.697
Weekends	-1.054
Saturday	-0.927
Sunday	-1.131
ANOVA F-statistic (6)	356.38***
Departure Hour	
Morning	-0.628
Lunchtime	-0.911
Afternoon	-0.800
Evening	-0.762
ANOVA F-statistic (3)	150.82***

Notes: All elasticity values are significant at the <1% level
**** indicates statistical significance at the 1% level*

Furthermore, the price elasticity of demand changes according to the departure hour. In particular, even if the value is always below one, the demand is more elastic during lunchtime (-0.911), whereas the lowest value (-0.628) is found for morning hours (Table 3). This result

highlights that flights early in the morning are more business oriented (Alderighi et al., 2016; Borenstein & Netz, 1999).

4.2.3. Route dimension

Figure 4 shows how the price elasticity changes across flight destinations. This dimension is of particular interest, as demand not only changes in relation to time but also with respect to the location. Cities often have different elasticity values unless they are rarely computed (Oum et al., 1992). In fact, considering all 21 departure routes, the price elasticity varies from the most elastic value of -1.915 for Split (SPU) to the most rigid value of -0.535 for Hamburg (HAM). Understanding the price elasticity of demand on different routes may give an idea of whether they are primarily business or leisure. Routes such as Split (SPU), Lisbon (LIS), Prague (PRG), and Bristol (BRS) are more leisure passengers-oriented, as their elasticities (absolute value) are higher than one. Hamburg (HAM), Berlin (SXF), London (LGW, LTN, and STN), Milan (MXP), and Genève (GVA), on the other hand, are usually more business-oriented destinations (elasticity lower than 0.7 in absolute terms). Our results are also consistent with the findings of Salanti et al. (2012), who develop a 'leisure index' to disentangle business and leisure routes. This index is based on the idea that LCCs implement intertemporal price discrimination, as business travellers, who are known to have a higher willingness to pay compared to leisure travellers, generally reserve their seats later in time (Salanti et al., 2012). Routes where airlines aim to strongly implement such discrimination are found to experience an increase in fares in the last 15 days prior to departure that is more than proportional with respect to airfares over the entire booking period. On this basis, Salanti et al. (2012) introduce the 'leisure index' as:

$$L_r = \frac{\sum_i (\beta_{1-90,i,r} - \beta_{1-15,i,r})}{I}, \text{ with } i \in I \quad (7)$$

where $\beta_{1-90,i}$ and $\beta_{1-15,i}$ are dynamic price indicators computed 90 and 15 days in advance, respectively, for each flight i on route r, based on the airfare formula in Malighetti et al. (2009, 2010):

$$P_{irt} = \frac{1}{\alpha_{ir}\,(1+\beta_{ir} \cdot t)}, \quad (8)$$

where P_{irt} is the price for a seat offered t days in advance for flight i on route r and α_{ir} is a constant parameter related to the average price level over the considered period. A low value of β_{ir} indicates a steady price trend over the booking period, whereas a high β_{ir} corresponds to a greatly significantly discounted fare on advance purchases. In detail, a highly negative leisure index L_r means that, in the last days before departure, fares tend to be higher than what can be

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expected given the overall trend, which suggests that during the last 15 days before departure, airlines aim to address consumers with a higher willingness to pay, i.e. business passengers (Salanti et al., 2012). Therefore, the more negative the leisure index, the more the route can be defined as a 'business-oriented route'.

Computing the same index, we find that the leisure index and the elasticity coefficient have a correlation value of 61%. As shown in Figure 4, all routes with higher elasticity values show a higher leisure index, with a few exceptions (e.g. Basel, Southend-on-Sea, and Genève). This result therefore corroborates our analysis showing that the level of the price elasticity can provide information on the different types of routes (business- or leisure- oriented).

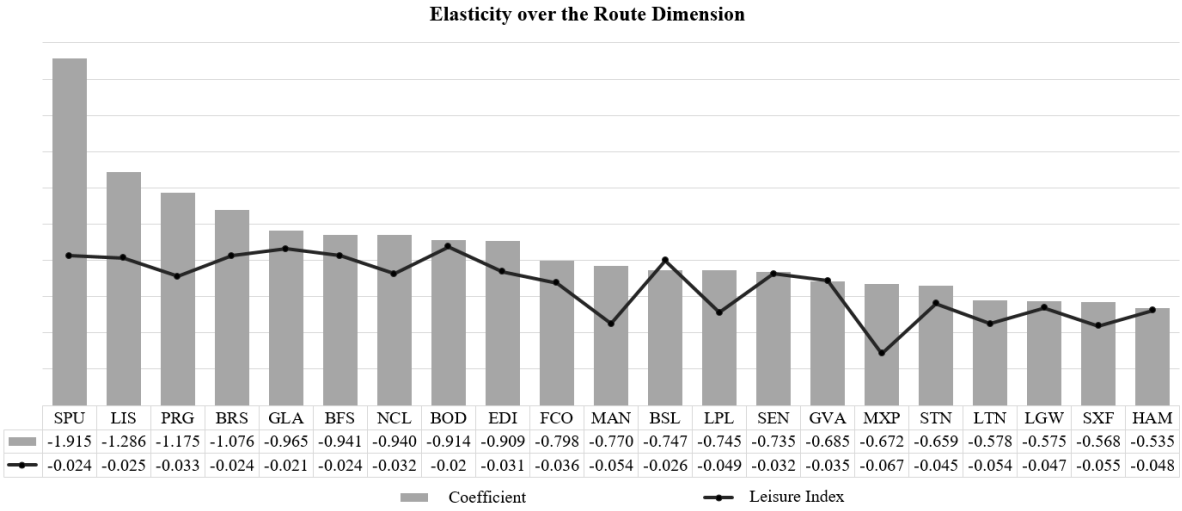

Figure 4 – Price elasticity value per route and the relative leisure index

Notes: All elasticity values are significant at the <1% level
The ANOVA F-statistic (20) is 73.75, significant at the <1% level

4.2.4. Seasonal dimension

On a broader time scale, the price elasticity of air travel demand is found to vary by the month of departure. The price elasticity is indeed higher during the summer months (-0.770) and lower during springtime (-0.738). Deepening the focus at the month level (Table 4), the highest price elasticity occurs in the month of July (-0.809), followed by August (-0.798), May (-0.797), and April (-0.792). Despite outcomes find evidence of differences in price elasticity, there are no large variations across months. This result could be due to the fact that spring and summer are not opposite seasons, and they might both be characterized by vacation time.

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Table 4– Price elasticity values per month

Elasticities over the Seasonal Dimension	
Spring	-0.738
March	-0.704
April	-0.792
May	-0.797
June	-0.677
Summer[a]	-0.770
July	-0.809
August	-0.798
September	-0.670
ANOVA F-statistic (6)	36.89***

Note: All elasticity values are significant at the <1% level
**** indicates statistical significance at the 1% level*
[a]*Summer starts on 21 June*

Given the existing variations in the price elasticity of demand across different dimensions (booking, flight, and route) we additionally observe the nature of these changes during *Spring* (from 8 March to 20 June) and *Summer* (from 21 June to 23 September) to better clarify which dimensions drive price elasticity. The results in Table 5 show that different seasons have different impacts on price elasticity. Specifically, during the summer months, passengers are more sensitive to prices. This result is consistent across all dimensions. The price elasticity of passengers reserving flights departing during spring more than two weeks in advance have on average a 8% lower elasticity than consumers reserving the same number of days in advance during the summer. Notwithstanding the fact that the price elasticity of demand does not overcome the unity threshold on different reservation days between the two seasons, the summer has an elasticity that is generally 6% higher than that of the spring, with the minimum difference during the weekends (+4%) and the maximum occurring specifically on Fridays (+8%). Considering the departing hour, the demand is always inelastic in the period from March to half June, whereas from 21 June to September, passengers travelling from 10 a.m. to 2 p.m. (i.e. non 'business hours') are highly price sensitive (-1.047). Furthermore, flights departing during the weekends have a 5% higher elasticity in the summer months, whereas the largest variations occur on Fridays (+9%) and Mondays (+8%).

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464 **Table 5 – Price elasticities by days in advance, booking day, departure day, and**
465 **departure hour over the spring and summer seasons**

Elasticities over the Seasonal, Booking, and Flight Dimensions		
	Spring	**Summer**
Booking Dimension		
Days in Advance		
1-5 days	-0.647	-0.669
6-10 days	-0.651	-0.681
11-15 days	-0.823	-0.865
>15 days	-1.537	-1.665
ANOVA F-Statistic (4)	221.51***	
Booking Day		
Working Days	-0.634	-0.674
Monday	-0.592	-0.639
Tuesday	-0.619	-0.651
Wednesday	-0.622	-0.661
Thursday	-0.645	-0.696
Friday	-0.689	-0.746
Weekends	-1.207	-1.252
Saturday	-1.277	-1.341
Sunday	-1.138	-1.175
ANOVA F-Statistic (7)	125.34***	
Flight Dimension		
Departure Day		
Working Days	-0.692	-0.657
Monday	-0.710	-0.769
Tuesday	-0.565	-0.540
Wednesday	-0.565	-0.610
Thursday	-0.599	-0.570
Friday	-0.669	-0.732
Weekends	-1.030	-1.086
Saturday	-0.897	-0.967
Sunday	-1.111	-1.157
ANOVA F-Statistic (7)	318.90***	
Departure Hour		
Morning	-0.697	-0.677
Lunchtime	-0.680	-1.047
Afternoon	-0.774	-0.836
Evening	-0.771	-0.751
ANOVA F-Statistic (4)	86.17***	

466 *Note: All elasticity values are significant at the <1% level*
467 **** indicates statistical significance at the 1% level*

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468 **Table 6 – Price elasticity values, routes, and number of flights over spring and summer**

Elasticities over the Route and Seasonal Dimensions					
Destination	**Spring**	**Summer**	**No. of Spring Flights**	**No. of Summer Flights**	**Flight variations[a]**
BFS	-0.812	-1.082	102	111	9%
BOD	-1.047	-0.779	92	93	1%
BRS	-1.089	-1.058	164	129	-21%
BSL	-0.784	-0.690	216	157	-27%
EDI	-0.717	-1.155	144	129	-10%
FCO	-0.838	-0.744	280	211	-25%
GLA	-0.692	-1.362	60	54	-10%
GVA	-0.712	-0.637	246	121	-51%
HAM	-0.632	-0.461	44	59	34%
LGW	-0.574	-0.577	484	425	-12%
LIS	-1.307	-1.263	45	40	-11%
LPL	-0.751	-0.737	199	172	-14%
LTN	-0.573	-0.585	366	328	-10%
MAN	-0.763	-0.777	187	175	-6%
MXP	-0.689	-0.648	384	287	-25%
NCL	-0.940		52		-
PRG	-1.326	-0.998	99	76	-23%
SEN	-0.730	-0.742	213	175	-18%
SPU	-0.978	-2.659	28	53	89%
STN	-0.648	-0.671	289	271	-6%
SXF	-0.557	-0.584	264	187	-29%
ANOVA F-Statistic (21)				73.98***	

469 *Notes: All elasticity values are significant at the <1% level*
470 **** indicates statistical significance at the 1% level*
471 [a] *Flight variations is computed as the percentage difference between the number of*
472 *summer and spring flights*

473

474 With respect to the price elasticity of demand across different routes in different seasons, the
475 elasticity values in Table 6 help in clarifying which routes can be considered as more business
476 or more leisure oriented throughout the seasons. In particular, from the previous Figure 4,
477 Bristol (BRS), Lisbon (LIS), Prague (PRG), and Split (SPU) are the most leisure-oriented routes
478 in our sample. However, by looking at Table 6, only Bristol (BRS), and Lisbon (LIS) have
479 elasticities greater than one during both the spring and summer months. The other destinations
480 vary according to the season. Specifically, Bordeaux (BOD) and Prague (PRG) are
481 characterized by highly price elastic passengers only during the springtime, whereas Belfast
482 (BFS), Edinburgh (EDI), Glasgow (GLA), and Split (SPU) are characterized that way only
483 during the summer. On the other hand, the remaining routes, such as Basel (BSL), Rome (FCO),

Genève (GVA), Hamburg (HAM), London (LGW, LTN, and STN), Liverpool (LPL), Manchester (MAN), Milan (MXP), Southend-on-Sea (SEN), and Berlin (SXF) can be defined as business-oriented routes since their elasticities are always below one. In order to avoid biased conclusions, we also check for variations in the number of flights per route in the two different seasons. Usually, the number of flights decreases by 18% during the summer. However, this decrease is mainly due to the closure of the Amsterdam-New Castle route and to the significant decrease in the number of flights for the Genève (GVA) route. Despite these variations, the number of flights remains almost the same between the two seasons.

5. Conclusion

Despite the importance of understanding the dynamics underpinning the price elasticity of demand in the air transport industry (Brons et al., 2002; Mumbower et al., 2014), only a few studies attempt to investigate this phenomenon, limiting their focus to the US context (e.g. Granados et al., 2012a; Granados et al., 2012b; Mumbower et al., 2014) and only examine a few dimensions across which the price elasticity of demand might vary (e.g. Mumbower et al., 2014). This study contributes to past empirical assessments by showing how the price elasticity of demand can also vary across the route and seasonal dimensions in the low-cost carrier industry in Europe. For this purpose, we rely on an extensive dataset of reservations and fares offered online by easyJet for flights during the period 8 March–23 September 2015.

Our results highlight that the overall price elasticity of demand is equal to -0.753, suggesting that easyJet targets a high proportion of business passengers. By deepening our analysis and looking at the booking, flight, route, and seasonal dimensions, we find that the response of demand to price changes is lower a few days before departure; during working days; in the morning, afternoon, and evening hours; during spring; and for certain routes (e.g. Hamburg-HAM, Berlin-SXF, London-LGW and LTN, and Milan-MXP). In contrast, the elasticity is greater than unity for the so-called 'leisure-oriented routes', such as Split (SPU), Lisbon (LIS), Prague (PRG), and Bristol (BRS); during weekends; and at lunchtime. Our findings are also confirmed when controlling for different seasons.

These results shed light on the different price sensitivities of leisure and business passengers. In fact, demand is inelastic for reservations that occur only few days before departure and during working days. These are the typical reservation conditions for business passengers (Alderighi et al. 2016; Mantin & Koo, 2010; Salanti et al., 2012), who usually book flights departing in the morning or after lunchtime and from Mondays to Fridays, and for

specific business routes (Salanti et al., 2012). During the summer, when the number of leisure passengers increases, the price elasticity values are instead higher.

To summarise, our work corroborates the general findings in the previous literature (Brons et al., 2002; Granados et al., 2012a; Granados et al., 2012b; Mumbower et al., 2014; Oum et al., 1992) by improving the analysis of the route and the seasonal dimensions and by focusing on the European context. In fact, even if the European and the US contexts have different features, the price elasticity variations in the European low-cost market are in accordance with those found in the US traditional (Brons et al., 2002; Granados et al., 2012a; Granados et al., 2012b) and low-cost (Mumbower et al., 2014) markets.

Furthermore, the different price elasticity values found in our analysis have managerial policy implications for different stakeholders, namely airlines, passengers, and tourism managers. On the supply side, our results might help airlines in setting new strategies by forecasting the effect of a potential change in their flight offerings in terms of departure times, days, and also destinations. Moreover, knowing whether passengers are price sensitive on a certain reservation day, for a flight departing on a particular day, at a specific hour, or to a specific destination could be used by air carriers to better implement their price-discrimination strategies, as offering discounts or raising airfares slightly influences the number of booked seats by passengers in the case of a low price elasticity. On the demand side, elastic routes are more likely to be associated with decreasing prices as the date of flight approaches given that airlines may find it advantageous to offer temporary discounts to stimulate demand and recover their expected booked quantity. Therefore, passengers informed about the leisure-level or the elasticity characterizing a destination could act strategically by choosing the best booking timing in order to minimize the ticket price paid. Interestingly, our findings could also help tourist managers in meeting the willingness to pay of incoming travellers. Indeed, by knowing the variations in the price elasticities of tourists according to the purchasing time and origin, hotel managers and other service providers can implement dedicated price discrimination strategies, which can help in their profit maximisation under capacity constraints (e.g. Weatherford & Bodily, 1992).

This study opens many avenues for future research. First, considering the plethora of easyJet flights departing from airports other than Amsterdam Schiphol, this analysis can be enriched by broadening the study to include new routes with a different business-leisure mix. Our findings indeed suggest that the price elasticity of demand changes across the different routes considered. Further, even if easyJet represents the European LCC framework well, our analysis could be corroborated by considering other European carriers. It is indeed well

recognised that each LCC has its own pricing strategy, with fares changing according to several factors, such as number of days in advance (e.g. Bergantino & Capozza, 2015; Dana, 1999; Salanti et al., 2012), flight characteristics (e.g. Alderighi et al., 2016; Salanti et al., 2012), and booking characteristics like the day of reservation (Mantin & Koo, 2010) or even the number of booked tickets (Cattaneo et al., 2016). Additionally, considering that intra-modal substitution plays an important role when analysing the price elasticity of demand (Brons et al., 2002), the work could be deepened by focusing on airports where two large LCCs operate contemporaneously. This analysis would enable the computation not only of the price elasticity of demand for a single airline but also of the cross-price elasticity, determining the consequences of price changes of LCC i on the demand variations of LCC j. Other improvements could be carried out by enlarging the sample, both in terms of time and distribution channels. As confirmed by our elasticity results (-0.738 and -0.770 during spring and summer, respectively), March-September spans two seasons that are not as different as the winter and the summer seasons are. Expanding the time period would mean analysing consumers with clearly different characteristics that can influence the price elasticities of demand over several dimensions. Further, as demonstrated by Granados et al. (2012b), passengers booking airfares through different reservation channels have different price sensitivities. In this sense, a comparative study across channels would shed light on the booking preferences of business and leisure travellers.

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