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The dynamics between price and demand of myopic and strategic consumers in the air transport industry

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Abstract

This thesis sheds light on the relationship between dynamic pricing strategies and consumer demand in the air transport industry. The work is structured around three main research questions, which explore revenue management implementation and the relative influence on consumers' purchasing behavior. The first research question extends the literature on airline pricing strategies by investigating the presence of quantity price discrimination of a leading European low-cost carrier, finding evidence of a two-part tariff pricing structure in offered fares (i.e., airfares are composed by a fixed fee per reservation and a variable component of price). Interestingly, the application of this kind of strategy is not linear in volume and it generates quantity discounts. Quantity discounts do not substitute the typical pricing discrimination strategies implemented by airlines, rather they are an additional way in which airlines price discriminate consumers. Second, to have an overview of the effectiveness of implementing price discrimination strategies, passengers' price elasticity of demand is investigated. Outcomes suggest that price elasticity of European low-cost passengers greatly varies across different dimensions (i.e., seasonality, booking and flight characteristics, and served markets). Specifically, price elasticity is higher for reservations made more days in advance, as well as for bookings and departures occurring at weekends. Moreover, flights taking off during lunchtime and in the summer period are characterized by more sensitive passengers with respect to other daily timings and during springtime. As a third step, since price variations are the main outcome of revenue management, their impact is quantified by considering an advanced measure of price volatility, which takes into account past and more recent price changes, as well as the predictability of fare changes over time. Empirical analyses reveal that with higher degrees of price volatility (above and beyond the predicted price trajectory), demand decreases coupled with a significant decrease in price elasticity. Intuitively, price volatility induces lower demand elasticity, whereby consumers may end up paying more, but possibly reducing the overall demand (given the higher price). This insight suggests the need to incorporate the effects of price volatility on consumers' demand into the classical revenue management model (Expected Marginal Seat Revenue), demonstrating its potential implementation benefit, while capturing the potential harm caused by the presence of strategic

consumers. Overall, this thesis gives new explanations on consumers' behaviour and timing of their purchases: i) consumers' knowledge of price discrimination strategies helps in their timing decision in order to pay a lower price; ii) acknowledging that only in markets where consumers are price sensitive it is beneficial to implement price drops, price elasticity estimates on different dimensions lead passengers to more easily identify the possibility that airlines plan price variations; and iii) consumers may take advantage of price fluctuations and wait for downward price adjustments.

Chapter 1- Introduction

Estimating and understanding how demand responds to prices is one of the core objectives of economic, marketing, and operational research studies. While demand is subject to a multitude of determinants, such as income, product quality, and consumers' preferences, price is widely recognized as one of the most important factors (Muth, 1961; Shepherd and Shepherd, 2003; Whitin, 1955). To this extent, this thesis aims to explore the relationship between demand and price dynamics in the context of revenue-managed goods.

In the classical revenue management setting, a fixed number of items are at the disposal of the firm to be sold to a segmentable stream of consumers who arrive sequentially over time (Gallego and van Ryzin, 1994; Feng and Gallego, 2000). The challenge faced by firms operating in this kind of setting is to maximise their profits by determining the proper prices to offer to different consumers over a finite time horizon (Talluri and var Ryzin, 2004). Numerous industries encounter such an environment, ranging from the air transport industry, which was the avant-garde in adopting and advancing the use of revenue management practices, via the hospitality and tourism industry, entertainment industry, and the advertising sector.

By focusing on the air transport industry, this thesis studies the way in which European low-cost carriers attempt to maximise their revenues following a revenue management strategy approach, where airfares are continuously revised to meet consumers' willingness to pay, expected demand, and seat capacity. First, it is analysed whether there are still unexplored forms of price discrimination applied by airlines. In details, the first research question of this work sheds light on the possibility that, next to the well-known price discrimination techniques, airlines implement a second-degree price discrimination, leading to quantity discounts. Certainly, the extent to which price discrimination strategies are successful depends on the way airlines implement them as well as on the impact of dynamic variation of prices on purchasing behaviour. A full understanding of the segments of consumers and their price sensitivities in a specific market is therefore decisive for a firm in order to maximise its profit. In this sense, this thesis focuses on the consumers' price elasticity of demand and on the different dimensions across which it varies. Specifically, the second and the third research questions of this work shed light on the characteristics that may have an impact on consumers' price elasticity. After exploring flight, booking, seasonal and market characteristics, the focus moves on an intrinsic consequence of revenue management approaches which may affect price elasticity: i.e., price volatility. Price fluctuations are indeed the major outcome that emerges as a result of implementing revenue management. Estimating accurate price elasticity values in light of price changes is pivotal to properly model consumers' purchasing behaviour and provide insights into the optimal pricing strategy that sellers should adopt (Belobaba, 2002; Bitran and Caldentey, 2003; Talluri and van Ryzin, 2004; Weatherford and Belobaba, 2002; Ziya et al., 2004).

All the proposed research questions are commented in light of the presence of strategic consumers, which is a topic of great interest in the recent literature (e.g., Li et al., 2014). Strategic consumers, defined as those consumers who strategically time their purchases in order to maximize value (Cachon and Swinney, 2009; Li et al., 2014), are recognised to have significant effects on revenues, as well as inventory management decisions (Cachon and Swinney, 2009; Li et al., 2014; Mantin and Rubin, 2016; Nair, 2007; Su, 2007). Information about this thesis' results can be exploited by both sellers and eventually consumers. Revenues greatly depend on a full understanding of how much a variation in prices would stimulate or reduce demand (Tellis, 1988). Similarly, consumers with additional information on price elasticities may leverage on this information to time their purchases in order to pay a lower price.[1]

To address the research questions, Chapters 3, 4, and 5 rely on a similar dataset which includes posted fares of easyJet flights from 45 to 1 day before departure. By means of a web crawler, unitary daily airfares are collected. Further, to gather information on the remained seat capacity at a certain day, it is checked the daily sold-out quantity in the 1-40 range. This download allows to map the unitary offered fare in relation to the booked quantity, as well

[1] Air transport consumers may leverage on different tools to get information on airlines pricing strategies. Even if common travellers are not supposed to read research papers, they can indirectly benefit from such results. Tolls which can be used by consumers are better described in Section 2.4.

as to compute the number of sold seats as the difference between the available seats at day $t+1$ and at day t. Moreover, fare details at a daily level facilitate the full understanding of the carrier pricing strategy and of the relative consumers' purchasing behaviour, in relation to time, market, seasonality, as well as other booking and flight characteristics.

The rest of this thesis is organised as follows. Chapter 2 briefly discusses the current literature on revenue management, the already studied forms of price discrimination strategies implemented by airlines, price elasticity estimates in the air transport industry, and strategic consumers. Chapter 3 focuses on the first research question and explores whether there exists a still unexplored form of price discrimination. Chapter 4 and Chapter 5 investigate passengers' price elasticity of demand in relation to different dimensions, analysing consumers' purchasing behaviour in relation to price fluctuations. Finally, Chapter 6 provides general concluding remarks.

Chapter 2– Literature review

With the aim to explore the price-demand dynamic interaction, this thesis takes the air transport industry as an example. This industry is characterized by intriguing features of interest to scholars examining different aspects of airlines' pricing strategies and their influence on consumer purchasing behaviour. First, the service offered by airlines, i.e., a seat on a specific flight, is perishable over a finite time horizon, thus once a flight departs, revenues from unsold seats are lost. Second, airlines are subject to capacity constraints based on the number of available seats per flight. Airlines also have high fixed costs, which are not modifiable in the short term. Thus, airlines need to act strategically in order to maximize load factors and average revenue per flight.

While in the long-term airlines may vary the number of seats offered to meet demand, by increase either frequencies or aircraft capacity, in the short-term airlines have to find a proper pricing strategy to maximize profits (Alves and Barbot, 2009). Indeed, once sales are opened, scheduling and aircraft selection is already programmed. Since, marginal cost of selling or adjusting fares is low profit maximization takes place through dynamic pricing aimed at revenue maximization per each flight (Belobaba, 1989). This approach has been studied in literature as revenue management, i.e. the procedure of selling products or services at the right time, to the right consumers, and at the right price (Weatherford and Bodily, 1992).

2.1. Revenue management

Revenue management can be defined as all the strategies and tactics used to maximise sellers' revenues, when the goods provided are limited in capacity and sales have to occur within a finite time horizon (e.g., Talluri and van Ryzin, 2004). There are different industries dealing with revenue management, varying from hotels, car rentals, and air transport; where the air transport one can be considered a leading example. The air transport industry has all the features that make revenue management techniques useful, namely the presence of consumer heterogeneity in terms of willingness to pay, the uncertainty characterizing demand, and the production inflexibility. Production inflexibility is due to capacity constraints (van Ryzin and

Talluri, 2004) and product perishability. Indeed, airlines face the problem of selling a predetermined number of tickets (depending on the aircraft capacity of each offered flight) within a fixed deadline, which corresponds to the departure date (Anjos et al., 2005).

Theory on revenue management recognizes three main different steps (Phillips, 2005): identification of customer segments and pricing decisions for each segment, setting and updating booking limits, and determining bookings to reject. The first phase is the most important, as it ensures a successful application of revenue management. Mainly, airlines distinguish among two kinds of consumers: leisure and high yield/business ones. With respect to business travelers, leisure ones are highly price sensitive, book earlier, are more flexible to departure and arrival times. These characteristics are used to segment the market, by relying on both product and price differentiation (see further details in Section 2.2). The second and third phases deal with booking policies. Revenue-managed goods are often organized in fare classes and sold at a price depending on revenue potential. A booking limit has the aim to control the amount of capacity that can be sold to a specific price at a certain point in time. Basically, a booking limit ensures that actual revenues at a certain price p are higher than futures one at a price $p + x$. Booking limits are continuously revised in function of expected and realized demand and they are decisive for the third step, where it is decided whether to accept or reject bookings for a certain price (McGill and van Ryzin, 1999). Further details on booking limits and the mathematical formulation they rely on are presented in Section 5.5, where it is presented the Expected Marginal Seat Revenue (EMSR) model.

Revenue management has two main variables to work with: price and quantity. Price choices comprehend decisions on price setting, price variations over different products, as well as price raises or mark-downs in function of time. Quantity decisions consist, among all, in deciding whether to accept or reject an offer and how many products or services to allocate to a certain fare class. These two decision variables often lead to two different kinds of revenue management, namely price-based and quantity-based revenue management. Substantially, in both cases revenue management techniques are applied, with the only distinction on whether airlines have more flexibility in prices with respect to quantities. Usually, traditional carriers are known to apply quantity-based revenue management, while literature on low-cost carriers focus on dynamic pricing as a result of price-based revenue management. Specifically, to respond to demand uncertainty, carriers tend to differentiate among consumers by applying the so-called dynamic pricing, where prices change according to different characteristics (e.g., time, competition, geographical context) to meet the heterogeneity in consumers' willingness to pay. Section 2.2 presents an overview on the main variables according to which airlines price discriminate.

2.2. Price discrimination

Generally, adopting a uniform pricing is inefficient, especially when dealing with perishable products. Price discrimination is defined as the strategy to charge different prices for the same good or service to different consumers (e.g., Pepall et al., 2008). There are three main approaches to price discriminate, namely first-, second-, and third- degree price discrimination. The first-degree price discrimination is rarely adopted, as it requires a perfect knowledge of consumers' willingness to pay. In this framework, the seller sets as many prices as the number of different units of product or service offered (Carrol and Coates, 1999, Shapiro and Varian, 1999). In the case of second-degree price discrimination, sellers do not have a full information about consumers' willingness to pay and offer different prices varying with the quantity sold. The seller therefore implements a 'menu-pricing' technique, where consumers are induced to self-select the menu to buy (Carrol and Coates, 1999). Finally, third-degree price discrimination, also called 'group pricing' allows sellers to segment consumers in groups, according to their reaction to price levels and price fluctuations.

Implementing price discrimination strategies is not harmless. Even if price discriminating is recognized to potentially improve sellers' profits, it has to be applied in an optimal way in order to avoid the risks of cannibalization and arbitrage. An imperfect segmentation of consumers according to their willingness to pay may lead to the phenomenon of cannibalization, where high-price consumers may find a way to pay lower prices. Furthermore, price differences may induce third parties to find a way to buy the offered product or service at the low price, then reselling it at high willingness to pay consumers below the market price, keeping the difference from themselves.

Literature on product and especially price discrimination in the air transport industries explores different ways in which it can be applied. The first method that airlines use to discriminate among passengers grounds on a different offered service: fares are found to vary according to the different service offered, thus letting higher quality services to be paid more. In this way, air carriers attempt to segment the market offering a different product which satisfy separately low- and highly- price sensitive passengers. However, the distinction between these two kinds of consumers is not so trivial, especially for low-cost carriers who are used to offer the same level of service for all passengers (Moreno-Izquierdo et al., 2015). This leads to a general complexity of implementing the so-called 'third degree price discrimination', that in the air transport industry is often revealed as different travel class (e.g., business vs economy) tickets. Accordingly, as it is difficult to directly observe consumers' price sensitivity, the way to discriminate between these two kinds of consumers is based on several factors, such as booking and flight features. The main way airlines attempt to price discriminate properly is called inter-temporal price discrimination.

Intertemporal price discrimination aims to differentiate between leisure and high yield/business passengers according to the timing at which they make a purchase. Specifically, highly price-inelastic business passengers are recognized to book just a few days before departure while price-elastic leisure travellers book with greater advance (Bergantino and Capozza, 2015). Since the 90s, intertemporal price discrimination is one of the most successful methods to earn profits; using this approach airlines price discriminate by offering advance-purchase discounts, thus distinguishing travellers according to their value of time (Dana, 1998). During the last decade, many researchers found evidence of intertemporal price discrimination and study how airlines apply it and what effects it has (e.g., Button and Ison, 2008; Malighetti et al., 2009; Piga and Bachis, 2007). Even if it is shown in different ways and named differently, intertemporal price discrimination is based on the so-called non-decreasing price commitment (Li et al., 2014), where price levels increase the last days before departure.

Along with intertemporal price discrimination, airlines attempt to find other ways to discriminate according to the willingness to pay. In an Internet selling framework, Bachis and Piga (2011) find evidence of price differences according to the currency at which the ticket is offered. Mantin and Koo (2010) show how airfares change according to the days at which seats are booked: since airlines expect more leisure-booking consumers at weekends and more business-booking passengers during weekdays, applying different prices in different week days helps in differentiating among passengers. Similarly, Puller and Taylor (2012) find a relation between prices and booking day, as well as advance, departure date, ticket restrictions, demand of flights. Other ways to discriminate can be according to the departure day and hour, the Saturday-night stayover, and the markets where the flight is offered (e.g., Escobari and Jindapon, 2014; Malighetti et al., 2009; Salanti et al., 2012).

Certainty, airfares level and the intensity of applied price discrimination cannot be independent from the context where they are applied. Accordingly, market concentration and competition are found to affect the ability to price discriminate. Stavins (2001) find a negative relationship between price discrimination and concentration on the American airlines market, thus implying the presence of a higher price discrimination on routes with more competition. Similarly, Giaume and Guillou (2004), by relying on ticket restrictions as a proxy of price discrimination, demonstrate that concentration has a negative effect on the level of prices. However, the lower the market concentration, the more price discrimination is applied. In contrast, Gerardi and Shapiro (2009) and Gaggero and Piga (2011), using the assumption that a monopolist is a price maker, provide evidence of a negative impact of competition on price discrimination and price dispersion.

2.3. Price elasticity of demand

Price discrimination strategies success strictly depends on the relative response of consumers' behaviour to prices and their changes with respect to different factors. While airlines' pricing strategies have been a topic of relevant interest over time, the estimation of 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 routes and passenger characteristics (Granados et al., 2012b). Basically, price elasticity explains the percentage change in purchased quantity with respect to a 1% change in price, and it can be influenced by several factors, such as household income, availability of substitute products and more generally consumers' preferences and perceptions. Although the definition of price elasticity is really simple, significantly different price elasticity estimates can be found for the same goods according to different dimensions. In the air transport industry, reports on price elasticity are generally limited to the aggregate market level revealing, for example, variation across markets (Gillen et al., 2003), or the impact of competition as a positive driver of price elasticity (IATA, 2008). In their comprehensive review summarizing 254 estimates taken from 21 different studies, Gillen et al. (2003) conclude that price elasticity can varies from -3.2 to 0, with an average value of -1.22. Interestingly, the report aggregates data according to three travel characteristics: the route length (short-haul vs long-haul), the domestic/international flight and the orientation towards business or leisure travellers of the flight. Generally, short/medium-haul passengers are more price sensitive than long-haul passengers, registering an average price elasticity of -1.150 and -0.857, respectively. Similarly, price elasticity of domestic long-haul markets is higher (-1.150) than international long-haul ones (-0.790). Finally, business passengers have a lower price elasticity than leisure passengers, presenting values of -0.730 (-0.265) and -1.150 (-0.993), respectively, for short- (long-) haul travels.
From the academic side, since the 1990s scholars report a variation of price elasticity of demand with respect to the nature of the travel (Brons et al., 2002; Oum et al., 1992) and the presence of substitute modes (Brons et al., 2002). In their meta-analysis, Brons et al. (2002) collect 37 studies on price elasticity for passengers, for an overall of 204 observations and examine their variation according to geographic, economic and demographic variables. Descriptive statistics find interesting variations in price elasticity according to the consideration of business classes, and distance. Specifically, passengers are more price elastic if travelling in economy class, and for long-term trips. Similarly, Oum et al. (1992) reports an average price elasticity of demand higher for leisure with respect to business travellers.

More recently, other studies explore the variation of air travellers demand elasticities with respect to different dimensions. 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. Interestingly, price elasticity of demand is found to vary across different sale channels (online vs. traditional) and different market segments (business vs. leisure). Their results highlight that 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.

Mumbower et al., 2014 focus on an LCC and show that, notwithstanding passengers are generally price elastic (-1.97 at the mean price), the demand is still inelastic for reservations made one to two days before departure (-0.57 at mean price). Moreover, departure time and day of the week, as well competition and booking day of the week seem to affect consumers' price elasticity of demand.

Table 2.1 summarizes all the previous studies on price elasticity of demand in the air transport industry.

Table 2.1 – Literature estimates of price elasticity

Authors	Year	Data source	Elasticity estimates	Studied dimensions
Oum et al.	1992	Literature review of previous studies	-3.30 : -0.40	• *Nature of travel*
Brons et al.	2002	Meta-study	-3.2 : 0.2	• *Route length (Short vs Medium haul)* • *Domestic/International demand* • *Business/Leisure purposes*
Gillen et al.	2003	Meta-study	-3.2 : 0	• *Nature of travel* • *Presence of substitute modes* • *Geographical, economic, and demographic characteristics* • *Distance*
Granados et al.	2012a	Booking data from an international airline	-2.28 : -0.34	• *Sale channels* • *Business/Leisure purposes*
Granados et al.	2012b	GDSs	-1.64 : -0.53	• *Business/Leisure purposes* • *Online/Offline channel*
Mumbower et al.	2014	JetBlue daily prices and seats map	-3.11 : -0.57	• *Departure time and day* • *Days to departure* • *Booking day* • *Competitor sales and promotions*

2.4. Strategic consumers

Literature recognises two main groups of consumers: myopic and strategic ones (Cachon and Swinney, 2009; Li et al., 2014). Myopic consumers are those who make purchases without strategically decide the timing of purchase (Li et al., 2014). Oppositely, strategic consumers strategically time their purchases, in order to pay as less as possible (Li et al., 2014). Basically, while the formers do not care about prices and their trend, the other ones, waiting before making their purchasing choice, toughly influence sellers' optimal pricing decision.

Several studies attempt to estimate the impact of strategic consumers on prices and sellers' revenues. Nair (2007) demonstrates how strategic consumers have a significant effect on optimal pricing and, by ignoring their presence, profit losses are large and economically considerable. Su (2007) shows that strategic waiting may even benefit the sellers if the non-myopic consumers are the low-value ones. Cachon and Swinney (2009) finds that retailers make different pricing and inventory management decisions if strategic consumers are present, stocking less and taking smaller discounts in order to lower gain drops.

In many industries, strategic consumers are those who recognise that in a certain point in time prices will drop, so they time their purchase accordingly (Mantin and Rubin, 2016). In the air transport industry, as explained in Section 2.2, price movements are harder to predict with respect to other markets. Indeed, airfares tend to increase as departure day approaches and waiting may include a double risk: stockout (i.e., no more seats are available) and increasing prices. By studying the presence of strategic consumers in the air transport industry, literature explores which are the instruments on which strategic consumers can rely on and estimates the percentage of strategic consumers existing in the market (Li et al., 2014; Osadchiy and Bendoly, 2015).

While assuming that consumers are fully informed on price markdowns is not realistic, nowadays consumers have great access to information and decision supporting tools that can help their strategic behaviour (Mantin and Rubin, 2016). One of the most famous tools which could be consulted by air travellers was *Farecast,* founded in 2003, sold to Microsoft in 2008 and finally included in *Bing Travel*. *Farecast* was one of the first website providing hints for deciding on the flight ticket purchase timing. Other websites nowadays provide advanced information on that. *Kayak* (www.kayak.com) and *skyscanner* (www.skyscanner.com) are the most popular. They offer suggestions on whether it is worth to make the purchase or wait and they allow to enable price drop alerts. More practical information are offered by *faredetective* (www.faredetective.com), where fare histories are shown across time, and by *hopper* (www.hopper.com), a mobile application which offers the same information. *Airhint* (www.airhint.com) provides travellers with predictions on price trends and drop probabilities. Among all web tools, it is the most complete for what concerns low-cost carriers, as it provides suggestion on price drop chance, price range in the selected period, the most frequent fare, as well as on whether it is a good moment to book or it is better to wait. Along with those tools, several important websites and magazines deal with this topic, suggesting for example which is the travelling day or hour with the lowest fare and the right time to purchase in order to save more money (e.g., The Economist, 2011; The Wall Street Journal, 2019).[2]

Given the multitude of information travellers can rely on, scholars try to demonstrate the presence of strategic consumers and to estimate their portion in the market. The only study which provides empirical estimates is the one of Li et al. (2014), who test their presence in the US arline market, observing a portion ranging from 5% to 19% proportion of strategic customers on average, depending on the booking time and the analysed market. Interestingly, Mantin and Rubin (2016) demonstrate that the information provided by web tools allow consumers who would like to act strategically to exploit the surplus from the carriers, leading to a maximum revenue loss of -3.2%.

[2] The Economist, 2011: https://www.economist.com/gulliver/2011/02/06/getting-the-cheapest-flights
The Wall Street Journal, 2019: https://www.wsj.com/articles/before-you-buy-plane-tickets-remember-these-four-things-11551881598

Chapter 3– A new form of price discrimination in the air transport industry: quantity discounts[3]

3.1. Introduction

As already specified in section 2.2, in the airline industry price discrimination is known to play a crucial role in setting profitable strategies. Traditional carriers have begun to maximise profits by use of a yield management approach, in which they provide different travel classes (business vs. economy) to suit passengers' various willingness to pay (Giaume and Guillou, 2004; Shapiro et al., 1999). However, this type of price discrimination, namely third-degree price discrimination, cannot generally be implemented by low-cost carriers (LCCs), since they tend to provide the same level of service for all passengers[4] (Gillen and Morrison, 2003; Moreno-Izquierdo et al., 2015). Instead, LCCs generally rely on intertemporal price discrimination (e.g. Alderighi et al., 2015), attempting to differentiate between highly price-inelastic passengers, who typically book just a few days before departure, and price-elastic travellers, who often book in advance, with fares increasing as the day of departure approaches (Bergantino and Capozza, 2015). Along with the other forms of price discrimination studied (see Section 2.2 for further details), a few recent studies have mentioned that airlines appear to vary fares depending on the number of tickets booked on the Internet by a single consumer, thus relying on nonlinear price discrimination (Alves and

[3] This chapter aims to respond to the first research question, exploring whether there exist other forms of price discrimination in the air transport industry that are not yet investigated by the literature. It is derived from the article 'Cattaneo, M., Malighetti, P., Morlotti, C., and Redondi, R. (2016). Quantity price discrimination in the air transport industry: The easyJet case. *Journal of Air Transport Management, 54, 1-8.*' I would like to thank my co-authors for the support received. I am responsible for all the changes in this chapter with respect to the published version.

[4] LCCs' service level is the same for all passengers, aside from the opportunity to board the aircraft first or to choose a specific seat.

Barbot, 2009; Lii and Sy, 2009). Still, no empirical studies on LCCs have thoroughly investigated the presence of quantity discounts[5] implemented as a part of nonlinear price discrimination.

This chapter contributes to the literature by providing evidence of LCCs' nonlinear price discrimination exemplified by easyJet's two-part tariff strategy. Specifically, ticket prices are composed of: i) a fixed fee (€17) per booking; and ii) a dynamic component that characterizes almost all LCCs' pricing strategies. Moreover, using a multivariate framework, the joint effect of these two components on unit price it is investigated at the single-flight level.

The analysis relies on a unique dataset, which includes fares booked on flights from the Amsterdam Schiphol airport (AMS) towards 20 European different destinations during the period between January and April 2015 (1,868 flights). Data on ticket prices and characteristics of the flights (destination airport, date of departure, and hour of departure) are gathered daily from easyJet's website. Unit prices are collected for reservations composed of 1 seat, 5 seats, and multiples of 5 seats, up to the maximum reservation that can be booked through easyJet's website, 40 seats.

The remainder of this chapter is organised as follows. After a brief literature review, Section 3.2 presents the theoretical model that merges the nonlinear price discrimination approach with the dynamic pricing structure implemented by LCCs. Section 3.3 describes the research methodology, Section 3.4 reports the results of the empirical analysis, and Section 3.5 summarizes the conclusions and proposes directions for further research.

3.2. Dynamic pricing strategy and quantity discounts in the LCC industry

3.2.1. State of the art

The literature regarding air transport economics has highlighted that identifying consumers' segments for low-cost carriers is arduous (Alves and Barbot, 2009). However, given the importance of applying price discrimination for airlines (see Section 2.2 for further details),

[5] In this study, quantity and volume discount are considered as synonyms (Philips, 1983).

there is evidence of price discrimination applied by LCCs, which mainly consists of fares dynamically increasing as departure day approaches (Alves and Barbot, 2009; Malighetti et al., 2009). In this way, low-cost carriers attempt to pursue their objective to discriminate passengers according to their willingness to pay, recognising that highly-price sensitive travellers are accustomed to booking tickets in advance in order to pay lower prices. In contrast, the majority of lower-price sensitive passengers usually decide to fly only a few days before the flight's departure, when ticket prices are higher.

Generally, the literature in the field (Alderighi et al., 2011; Malighetti et al., 2009) expressed the unit price of a seat on a flight as follows:

$$\mathrm{P_{it}}(1) = \mathrm{f}(\mathrm{a_{it}}, \mathrm{d_{it}}, \mathrm{c_i}) \tag{3.1}$$

in which the unit price for a seat, purchased by a single consumer at time t, on a flight on route i ($\mathrm{P_{it}}(1)$), is a function of the number of days of advance booking at time t (a_{it}) (e.g. Alderighi et al., 2011; Bergantino and Capozza, 2015; Malighetti et al., 2009), the number of seats available at time t (d_{it}) (Alderighi et al, 2011), and other characteristics of the carrier and route (c_i), such as the route concentration (Giaume and Guillou, 2004; Malighetti et al., 2009; Moreno-Izquierdo et al., 2015; Stavins, 2001), the size of the destination airport, (Malighetti et al., 2009, 2010; Salanti et al., 2012), and the destination's gross domestic product (GDP) (Malighetti et al., 2009, 2010; Moreno-Izquierdo et al., 2015; Salanti et al., 2012).

Although the topic has received much attention during the past decade (Alderighi et al., 2011; Dana, 1998; Li et al., 2014), few studies have suggested that fares change according to the number of tickets reserved by a single individual (Lii and Sy, 2009). An experiment carried out by Alves and Barbot (2009) to look for changes in unitary prices with respect to quantity reported the presence of surges in prices offered by Ryanair for flights from London-Stansted to Alicante during November 2007: Per-seat prices varied from £49.99 for 14 seats up to £149.99 for 21 reserved seats. However, no studies have thoroughly analysed the way in which LCCs utilize nonlinear price discrimination, in which the unit fare changes according to the quantity of seats being booked by a single consumer. This chapter provides evidence of how LCCs discriminate passengers by offering quantity discounts, thus falling into the nonlinear price discrimination case (Armstrong and Vickers, 2010).

3.2.2. Two-part tariff price discrimination

Nonlinear price discrimination is usually applied by means of a two-part tariff strategy, thus introducing a fixed, per-booking fee (i.e. a charge that does not depend on the number of seats included in the booking), accompanied by a variable unitary price.

Applying the typical two-part tariff rationale to airlines' dynamic pricing strategies, the resulting total fare is made up of two components:

$$\mathrm{P_{it}(q)} = \overline{\mathrm{p_{it}^{v}}}\mathrm{q} + \mathrm{F} \tag{3.2}$$

in which the total amount of money paid by a single consumer at time t for a flight reservation consisting of q seats on route i ($\mathrm{P_{it}(q)}$) is a function of the average variable price component charged to a consumer booking one seat ($\overline{\mathrm{p_{it}^{v}}}$)[6], and the fixed fee (F). The quantity discount becomes evident when considering the unit price $\mathrm{p_{it}(q)}$ (Ho and Zhang, 2008) as equal to $\overline{p_{it}^{v}} + F/q$. Due to the complexity of the LCCs' pricing system, $\overline{\mathrm{p_{it}^{v}}}$ is not a fixed, easily computable variable. In fact, it depends on different factors, such as the number of seats booked, as well as the other attributes ($\mathrm{a_{it}, d_{it}, c_i}$) previously described.

Accordingly, the unit price is ultimately equal to the following:

$$\mathrm{p_{it}(q)} = {}^{\mathrm{P_{it}(q)}}/_{\mathrm{q}} = \overline{\mathrm{p_{it}^{v}}}(\mathrm{q; a_{it}, d_{it}, c_i}) + \mathrm{F/q} \tag{3.3}$$

Considering the interdependence between the number of seats that are available at the time of booking and the price at which the seats are offered (Alderighi et al., 2015; Escobari et al., 2012; Li et al., 2014), when a consumer books two or more seats, rather than just one, two effects arise simultaneously. On one side, the component d_{it} brings about more rapid saturation of the flight, which may cause the price for the remaining seats to increase. On the

[6] For the sake of clarity, p_{it}^{v} in Equation 3.2 represents only the variable component, while $P_{it}(1)$ in Equation 3.1 stands for the entire unit price. This allows to make explicit the presence of a fixed component, F, which has not been yet highlighted in the previous literature.

other side, the F/q component causes the unit price to decrease, because the fixed component of the total booking fare is divided among a greater number of reserved seats. Hence, when the effect of F/q prevails over the effect of d_{it}, the unit price for a single consumer reserving more than one seat is lower than the unit price for a single booked seat; this is a quantity discount.

The objective is to identify whether and how an average percentage quantity discount ($\overline{\mathrm{D}_{\mathrm{it}}}(\mathrm{q})$) is present, by use of the following formula:

$$\overline{\mathrm{D}_{\mathrm{it}}}(\mathrm{q}) = \frac{\mathrm{p}_{\mathrm{it}}(1)-\mathrm{p}_{\mathrm{it}}(\mathrm{q})}{\mathrm{p}_{\mathrm{it}}(1)} \tag{3.4}$$

in which $\mathrm{p}_{\mathrm{it}}(1)$ and $\mathrm{p}_{\mathrm{it}}(\mathrm{q})$ (see Equation 3.3) are the unit fares offered to a single consumer reserving 1 or q seats, respectively, at time t for a flight on route i.

In this regard, easyJet represents a valid example. In addition to having instituted a dynamic pricing strategy according to advance booking (Koenigsberg et al., 2008; Malighetti et al., 2015; Salanti et al., 2012), the company has stated that it charges a €17 fixed fee per reservation[7], automatically divided among the number of seats booked in a single reservation.

3.3. Research Design

In order to empirically analyse the effects of the applied two-part tariff strategy under a typical LCC's framework, in this section it is investigated the existence of quantity discounts in the easyJet case (Section 3.3.2), after a brief description of the sample and data collected. Second, by relying on single-flight observations, the determinants of the value of the quantity discount implemented by easyJet are explored (Sections 3.3.3); these include the number of days in advance of departure the consumer books the reservation, the number of seats that are available at the timing of booking, and the level of competition, in addition to features of the destination airport.

[7] This information is available at *http://www.easyjet.com/en/terms-and-conditions/fees-and-charges*.

3.3.1. Sample and data

Data on daily Internet fares for 1,868 flights scheduled by easyJet and departing from AMS towards 20 European destinations were collected between 8 March 2015 and 22 April 2015[8]. Booking fares were collected daily from the easyJet website during the 45 days prior to each flight. The booking fare values (1,133,092 unit fare records) reflect the full prices paid by passengers for one-way trips, including easyJet's standard tariffs, airport charges, and other compulsory taxes and fees. Data was also collected about flight characteristics (destination, departure date, and departure hour), the date on which each fare was collected, and unit prices for reservations of 1 seat, 5 seats, and multiples of 5 seats up to the easyJet's website maximum of 40 seats. To gather the exact number of seats available on a specific flight at the time of the reservation, it is checked the daily sold-out quantity in the 1-40 range. In particular, when the flight was sold-out for a specific quantity *n* (a multiple of 5), it is controlled for the fare offered for n-1 seats, up to the number of seats for which that price was available. The ultimate number of seats for which the price was available thus represents the number of available seats.

Information was gathered from various sources: i) Unit fares were obtained from easyJet's website; ii) the annual number of total passengers was obtained from the website of each destination airport; iii) the GDP per capita of each destination's surrounding area was obtained from Eurostat and the Organisation for Economic Co-operation and Development (OECD) library; iv) the share of flights operated by easyJet compared to its competitors was obtained from AMS's website.

3.3.2. The relation between price and quantity

Given the two opposite effects potentially affecting unit price, namely the two-part tariff and the saturation of available seats, this section examines the existence of a quantity discount -

[8] These 20 European destinations are as follows: 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 Geneva (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.

a percentage discount in unit price for reservations composed of a larger number of seats. Specifically, the dataset helps determine the number of seats in a reservation at which easyJet offers the lowest unit fare.

Reporting the proportion of reserved seats at which it is offered the minimum daily unit fare for reservations of 1 seat, 5 seats, and multiples of 5 seats, up to easyJet's website maximum of 40 seats, Figure 3.1 and Table 3.1 highlight that the minimum daily unit price is generally offered when 5 seats are booked in a single reservation (74% of the 76,195 daily reservations) and that the price for single-seat bookings is the cheapest in only 4,169 cases (5% of the daily 76,195 reservations). Moreover, the unit prices for 1 seat and 5 seats are almost never equal (they are equal in only 1% of the cases), and the latter is rarely (only 4% of the cases) higher than the former. For even greater numbers of reserved seats, the quantity discount decreases: The cheapest daily unit fares are for reservations of 10 seats in 14% of cases but for reservations of 15 seats and 20 seats only in 6% and 1% of cases, respectively. There are no cases in which booking more than 20 seats in a single reservation gives the cheapest daily unit fare. Interestingly, this evidence suggests that unit prices are significantly lower for reservations that include 5 seats than for single-seat reservations. As shown in Figure 3.1, a U-shaped relationship exists between average unit prices and the number of seats booked in a single reservation. This finding confirms the expectation of how $\mathrm{p_{it}(q)}$ varies according to the booked quantity: The effect of the F/q component prevails over the effect of the saturation of the number of available seats (d_{it}), up to 5 seats booked in a single reservation.

In order to obtain the same average unit price (€84) for a multi-seat reservation as for a single-seat reservation, it is necessary to book more than 20 seats in a single booking. The average unit prices for 5 seats and 10 seats are equal to €75 and €79, respectively.

Next, it is tested whether quantity discounts are related to the number of seats available, to the number of days in advance of departure the reservation is being booked, or to other flight characteristics, such as departure time. Figure 3.2 illustrates that for various numbers of available seats (from 5 seats to 10 or more seats), the lowest fare is still usually associated with reservations of 5 seats. Concerning the effect of advance booking, Figure 3.3 shows that, on average, in 60% of the cases the lowest fare is associated with reservations of 5 seats, almost independently from the number of days in advance the booking occurs.

Table 3.1 – Descriptive statistics of unitary fares according to the number of reserved seats

No. Of reserved seats	Average fare (€)	Max fare (€)	Min fare (€)	Cases in which the minimum price is offered	Percentage of cases in which it is offered the minimum fare
1	83.5730	420.99	24.99	4,169	5.47%
5	73.0163	408.99	12.99	56,180	73.73%
10	74.8030	284.29	11.49	10,863	14.26%
15	78.5626	286.79	10.99	4,289	5.63%
20	83.1418	288.09	10.74	575	0.75%
25	87.7946	288.87	10.99	76	0.10%
30	92.4266	279.72	11.16	15	0.02%
35	96.6717	285.91	11.73	13	0.02%
40 or more	100.5045	290.55	12.27	15	0.02%

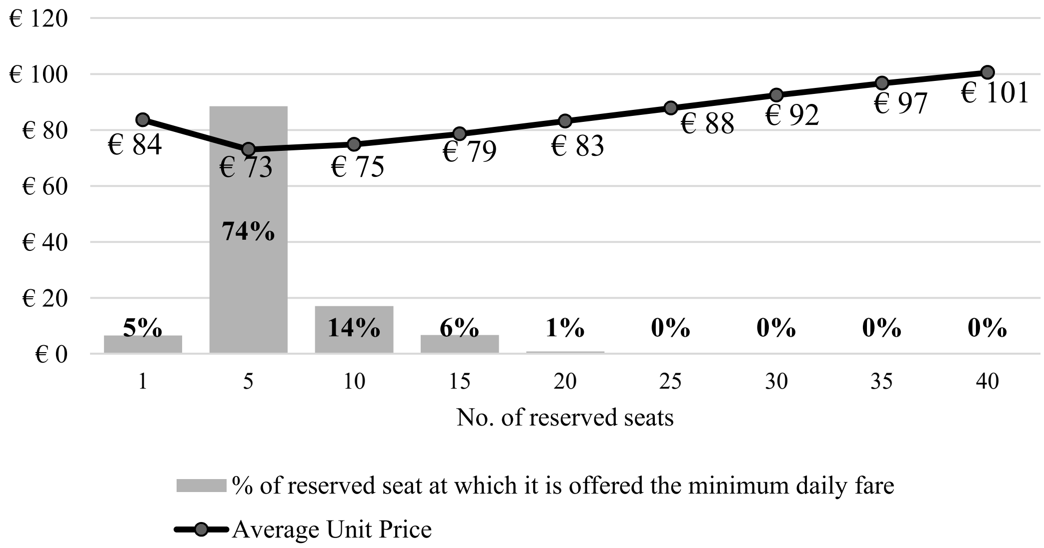

Figure 3.1 - Average unit fare and proportion of reserved seat at which it is offered the minimum daily fare

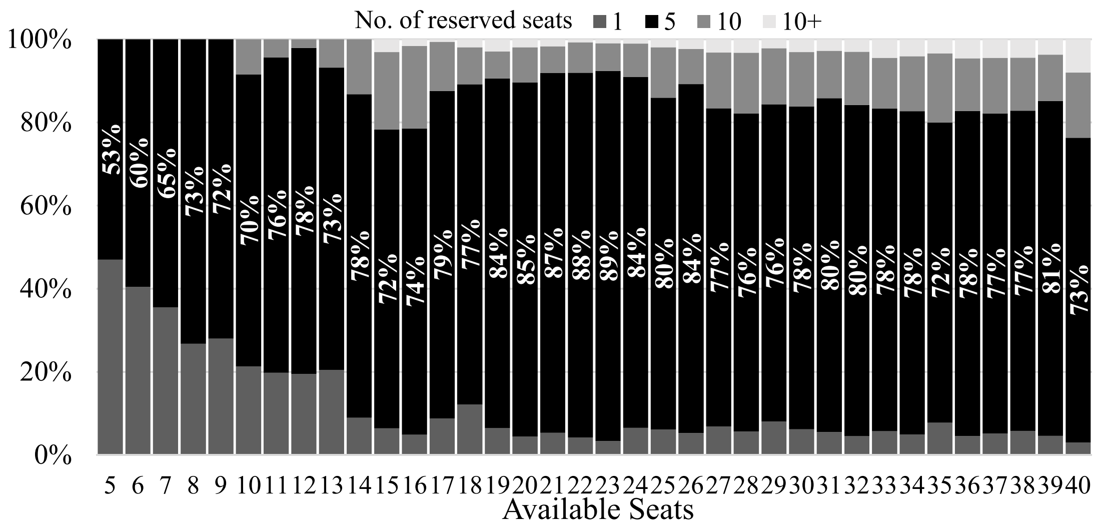

Figure 3.2 - Proportion of reserved seats at which it is offered the minimum daily fare, by available seats

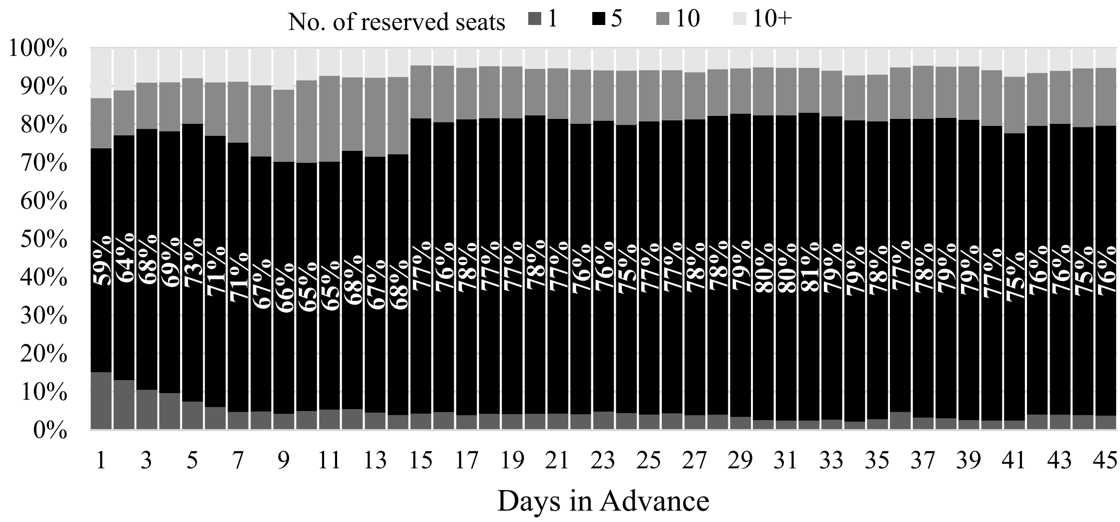

Figure 3.3 - Proportion of reserved seats at which it is offered the minimum daily fare, by advance booking

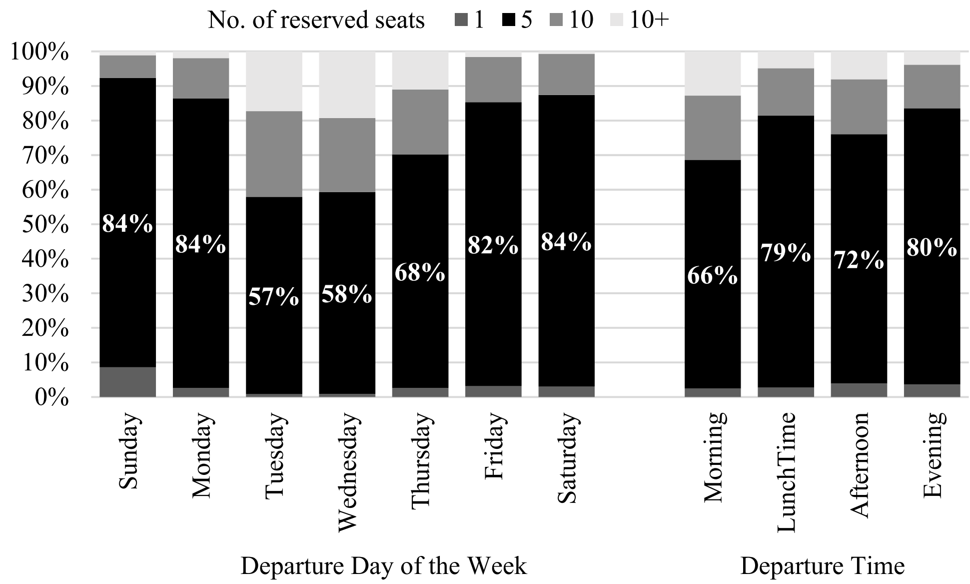

Figure 3.4 - Proportion of reserved seats at which it is offered the minimum daily fare, by departure day and day-time

Even when varying the departure day of the week or hour, the minimum fare is still associated with reservations of 5 seats. As illustrated in Figure 3.4, in more than 50% of cases the lowest fare is associated with reservations of 5 seats; by day of the week, this proportion ranges from 57% on Tuesdays to 84% on weekends. Figure 3.4 also shows that quantity discounts are greater during weekends (including Monday) and smaller during mornings. The high occurrence of minimum daily unit fares in presence of 5 reserved seats during weekends suggests that easyJet offers a type of 'family discount' (a cheaper unit fare for groups of 5 people in the same booking). During mid-week (Tuesday, Wednesday, and Thursday), the lowest unit fare is more frequently associated with larger groups.

3.3.3. The value of the discount and its determinants

Since evidence shows that the highest discounts are usually associated with reservations of 5 seats (74% of the cases), the 5-seat discount is used as the dependent variable in the following empirical analysis. This average percentage discount, based on Equation 1.4, is computed as follows:

$$\overline{\mathrm{D_{it}}}(5) = \frac{\mathrm{p_{it}}(1)-\mathrm{p_{it}}(5)}{\mathrm{p_{it}}(1)} \tag{3.5}$$

in which $\mathrm{p_{it}}(1)$ and $\mathrm{p_{it}}(5)$are the unit prices offered by easyJet at time t for a 1-seat and 5-seat reservation, respectively, for a flight on route i. On average, the results show a 5-seat quantity discount of €9.48 per seat, which accounts for 14% of the single-seat reservation fare.

Figure 3.5 shows how fares for various reservation sizes and the related average percentage quantity discount varies in relation to the number of advance booking days. Given the LCCs' intertemporal price discrimination strategy, average unit prices for reservations of 1, 5 or 10 seats increase as the departure date approaches. That variation ranges from minimums of €70, €60, and €63 at 45 days before departure to maximums of €115, €108, and €100 on the day before departure for 1-, 5- and 10-seat reservations, respectively. The average unit price for 10-seat reservations ranges between the unit price of 1-seat and 5-seat reservations until the 7$^{\text{th}}$ day before departure, while afterwards it is lower. This exception may be due to the fact that during the last days before departure, data are limited to routes having a higher spare capacity (Alderighi et al., 2015). Corresponding to those average unit prices, the 5-seat percentage quantity discount decreases from 17% (€9.95) at 45 days before departure to 8% (€7.76) on the day before departure.

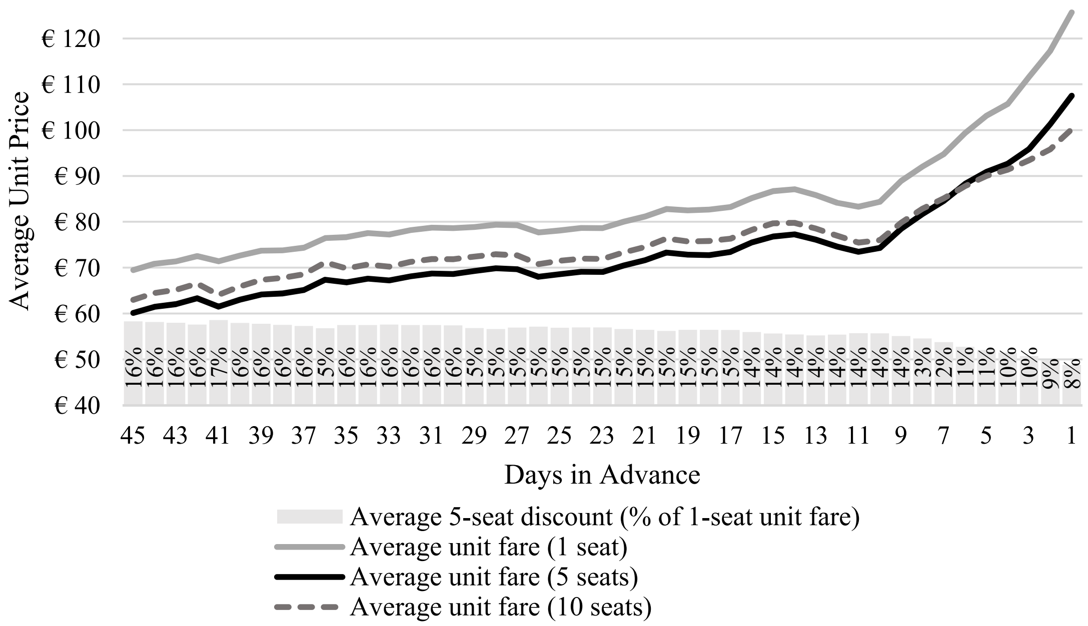

Figure 3.5 - Average 5-seat discounts and unit fares for 1-seat, 5-seat, and 10-seat reservations, by advance booking

Having illustrated the presence of the easyJet's 5-seat quantity discount, their determinants are investigated by using the following pooled ordinary least squares (OLS) model with robust standard errors[9], including departure-date dummy variables:

$$\overline{D_{it}}(5) = \alpha X_{it} + \beta Z_i + \gamma T_i + \varepsilon_{it} \tag{3.6}$$

in which $\overline{D_{it}}(5)$ is the percentage average 5-seat quantity discount enjoyed by a consumer when reserving 5 seats rather than only 1 seat in a single reservation at time t for a flight on route i, as detailed in Equation 3.5; the X_{it} vector represents a set of time-variant explanatory

[9] A pooled ordinary least square model is preferred because of the time varying and routes characteristics of the dataset. In particular, a panel approach is not used since each observation differs not only in terms of departure day and route, but also in terms of departure hour and advance booking.

variables at time t; Z_i represents a set of time-invariant explanatory variables for route i;T_i is a vector of dummy variables for departure date; and ε_{it} is the error term.

Relying on previous literature (Alderighi et al., 2011; Bergantino and Capozza, 2015; Giaume and Guillou, 2004; Malighetti et al., 2009, 2010, 2015; Moreno-Izquierdo et al., 2015; Stavins, 2001) the following potential time-variant and time-invariant determinants of quantity discounts are selected.

Time-variant explanatory variables:

- Five dummy variables that identify the number of available seats on the flight at the time of the reservation. Respectively, they are equal to 1 when the number of available seats is between 5 and 9 (*AS5-9*), between 10 and 19 (*AS10-19*), between 20 and 39 (*AS20-39*), and greater or equal to40 (*AS≥40*). The reference case is the case in which the number of available seats is between 1 and 4 (*AS1-4*).
- *Advance* is the number of days in advance of departure the reservation is booked.
- *DepWeek* is a dummy variable equal to 1 if the departure date is on a weekday (i.e. Monday through Friday).
- Four dummy variables that identify the hour of departure. Respectively, they are equal to 1 when the departure time is between 11 a.m. and 1.59 p.m. (*LunchTime*), between 2 p.m. and 5.59 p.m. (*Afternoon*), and between 6 p.m. and 9.59 p.m. (*Evening*). The reference case is the case in which the departure time is between 7 a.m. and 10.59 a.m. (*Morning*).

Time-invariant explanatory variables:

- *Distance* from AMS to the destination airport (in thousands of kilometres).
- The number of total passengers (*Passengers*) at the destination airport in 2014 (in millions).
- The GDP per capita (*GDPperCapita*) of the destination's surrounding area (NUTS 3 classification level), at 2014 market prices, measured in million Euros.
- The market share of easyJet on the route, defined as the number of flights operated by easyJet divided by the total number of weekly flights for a specific route in 2015 (*MarketShare*). Specifically, this variable is computed for each of the 21 routes

considered, independently from the fact that the city of destination is the same for different airports (London case: LGW, LTN and STN).

3.3.4. Descriptive statistics

Table 3.2 reports summary statistics for the dependent and explanatory variables included in the model and described in section 3.3.3. The average percentage discount $\overline{\mathrm{D}_{\mathrm{it}}}(5)$ as computed in Equation 3.5 varies from -52% on the 14th of March for the flight to Rome-Fiumicino departing on the 10th of April, to a maximum of 48% for reservations booked from the 20th of February to the 3rd of March for flights departing on the 10th and 17th of March for Hamburg. The percentage discount has an average value of 14%. The majority of flights are scheduled for departure during the morning (33%) or evening (39%), and fewer flights (28%) depart between 11 a.m. and 6 p.m. (lunchtime and afternoon). Airport sizes, in terms of total annual passengers, vary from more than 38 million (Rome-Fiumicino and London-Gatwick) to fewer than 3 million (smaller airports such as Southend and Belfast). The average number of total annual passengers at the 20 destination airports included in this study is approximately 17 million. On average, the length of a route is approximately 580 kilometres. The longest distances, almost 2,000 kilometres, are for the Lisbon and Rome-Fiumicino routes, and the shortest distances are for flights towards Great Britain (all of the London airports) and Hamburg, Germany. The average market share for easyJet on the routes studied is 60.5%, ranging from 7.7% for the Lisbon route to 100% for the routes to Belfast, Liverpool, London-Luton, Milan-Malpensa, Southend, London-Stansted, and Berlin-Schoenefeld, where easyJet is the only airline that operates. Lastly, the average GDP per capita of the destination's surrounding area is approximately €35,000 per capita, with the highest being €56,000 for Switzerland.

Table 3.2 - Summary statistics for the variables in the model

Variable	Mean	Std. Dev.	Minimum	Maximum
Discount	0.144	0.092	-0.516	0.480
AS1-4	0.013	0.114	0	1
AS5-9	0.018	0.134	0	1
AS10-19	0.059	0.235	0	1
AS20-39	0.910	0.287	0	1
AS≥40	0.744	0.437	0	1
Advance (days)	23.257	12.970	1	45
DepWeek	0.753	0.431	0	1
Morning	0.326	0.469	0	1
LunchTime	0.090	0.286	0	1
Afternoon	0.199	0.399	0	1
Evening	0.386	0.487	0	1
Distance (thousands of km)	0.579	0.284	0.291	1.847
Passengers (millions annually)	17.407	12.771	1.100	38.507
MarketShare (%)	60.515	37.370	7.692	100
GDPperCapita (thousands of €)	35.453	9.553	19.949	55.900

3.4. Results

Table 3.4 reports the results of the pooled OLS regression. Quantity discounts are positively and significantly associated with the number of seats available at the time of booking, suggesting that the fewer seats available, the smaller is the discount offered by easyJet. For example, in the case when 5-9 seats are available at the time of booking, the 5-seat discount increases of 1.81% compared to the case of 1-4 seats available. This increase is equal to 8.73% if 20-39 seats are available at the time of booking. For more than 40 seats available, there is still an increase in the quantity discount, but it is only 3.67%. This is in line with what is shown in Table 3.3, where discounts are positively correlated with *AS20-39* and *AS≥40,* while correlations with the variables representing a lower availability of seats are negative. Interestingly, when passengers book their tickets earlier, they receive greater quantity discounts, all else being equal. In terms of magnitude, compared to the number of seats available, the number of days the reservation is booked in advance of the departure date plays a marginal role in determining the quantity discount.

The departure days of the week cause significant variation in the magnitude of the quantity discount. Specifically, flights departing on Monday through Friday have discounts of almost 5%. Similarly, compared to flights departing in the morning, those departing at lunchtime, in the afternoon or during the evening register lower discounts. Focusing on the set of time-invariant variables, the quantity discount is negatively correlated to the distance between AMS and the destination airport, with the effect ranging from -2% in the case of a 291 km route (Southend) to -12% for an 1,847 km route (Lisbon). The negative relationship between quantity discount and distance may suggest that higher marginal costs for longer routes limit the possibility for easyJet to easily implement price discrimination (Malighetti et al., 2015).

At the same time, the scope for pricing to stimulate new traffic is indeed more limited for long-haul routes than for short haul routes (Francis et al., 2007), since passengers flying long-haul routes have generally lower price elasticities (Gillen et al., 2003). For short routes, the fixed component of the booking price (€17) represents a higher proportion of the total fare and thus increases the intensity of quantity discounts.

Table 3.3 – Correlation matrix of the variables included in the model

	Discount	*AS5-9*	*AS10-19*	*AS20-39*	*AS≥40*	*Advance*	*DepWeek*	*LunchTime*	*Afternoon*	*Evening*	*Distance*	*Passengers*	*Market Share*	*GDP perCapita*
Discount	1													
AS5-9	-0.1653	1												
AS10-19	-0.2027	-0.0342	1											
AS20-39	0.2734	-0.4348	-0.7934	1										
AS≥40	0.3500	-0.2332	-0.4256	0.5364	1									
Advance	0.1797	-0.2039	-0.3469	0.4517	0.6520	1								
DepWeek	0.3156	-0.0243	-0.0637	0.0682	0.1484	-0.0002	1							
LunchTime	-0.0106	-0.0048	0.0110	-0.0025	-0.0194	-0.0028	0.0362	1						
Afternoon	-0.0184	0.0016	0.0005	0.0026	0.0087	0.0055	-0.0643	-0.1565	1					
Evening	-0.1611	0.0160	0.0180	-0.0319	-0.0396	0.0003	0.0241	-0.2492	-0.3946	1				
Distance	-0.2446	0.0156	0.0371	-0.0466	-0.0809	0.0012	-0.0444	0.0353	-0.0628	0.0236	1			
Passengers	-0.0567	-0.0207	-0.0330	0.0465	0.0788	0.0042	0.0062	-0.1058	0.0469	-0.0052	0.1174	1		
MarketShare	0.0691	-0.0128	-0.0237	0.0348	0.0632	-0.0049	0.0234	0.0839	-0.0314	-0.0104	-0.4199	-0.1637	1	
GDPperCapita	0.1544	-0.0209	-0.0363	0.0500	0.0716	0.0013	0.0058	-0.0350	0.1996	-0.1357	-0.0972	0.1782	-0.2223	1

Table 3.4 - The determinants of quantity discount

Variable	Coefficient	Robust standard errors	P-value
AS5-9	0.0181**	(0.0056)	0.0013
AS10-19	0.0559***	(0.0053)	0.0000
AS20-39	0.0873***	(0.0053)	0.0000
AS≥40	0.0367***	(0.0007)	0.0000
Advance	0.0001***	(0.0000)	0.0000
DepWeek	0.0487***	(0.0028)	0.0000
LunchTime	-0.0177***	(0.0009)	0.0000
Afternoon	-0.0289***	(0.0008)	0.0000
Evening	-0.0340***	(0.0006)	0.0000
Distance	-0.0001***	(0.0000)	0.0000
Passengers	-0.0006***	(0.0000)	0.0000
MarketShare	-0.0120***	(0.0008)	0.0000
GDPperCapita	1.1836***	(0.0294)	0.0000
Constant	0.0709***	(0.0058)	0.0000
Number of observations		75,315	
R-squared		0.4628	
F-statistic		1072.06	

Notes: the regression estimated by use of the ordinary least squares (OLS) method. ***, **, *, and $^{+}$ indicate significance at the less than 0.1%, 1%, 5%, and 10% levels, respectively.

The size of the destination airport, in terms of the annual number of total passengers, seems not to play a crucial role, given the small magnitude of its coefficient. Even considering the largest number of passengers (38.5 million for Rome-Fiumicino) the quantity discount decreases by about 2%. The market share variable is highly significant, suggesting an average 0.12% decrease in quantity discounts for each 10 percentage-point increase in easyJet’s market share for that route. Therefore, it seems that, consistent with the findings of Giaume and Guillou (2004) and Stavins (2001), the greater the competition and the consequent pressure on prices (Gudmundsson, 2002), the greater the attempt by airlines to price discriminate. This conclusion is also consistent with the findings of Borenstein (1989), who specifies how a greater market share on a route allows airlines to increase airfares, and of Malighetti et al. (2015) who highlight, specifically for the case of easyJet, how competition reduces average fares while increasing the intensity of dynamic pricing. Finally, GDP per capita of the destination's surrounding area is positively associated with the quantity discount. Basically, the quantity discount increases with the GDP per capita of the destination: A €10,000 increase in GDP per capita results in an increase of approximately 1 percentage point in the discount. This result may suggest that easyJet is more interested in discriminating passengers who travel to richer areas.[10]

To conclude, results confirm the expectations about discount's changes in relation to demand shocks, since the variation of the 5-seat discount is aligned with the usual pricing strategy of LCCs already studied in literature. Specifically, the 5-seat discount decreases with bookings closer to departure date, when, all things being equal, demand shocks usually generate substantial increases in prices (Li et al., 2014). From a consumer's point of view, discounts seem to be addressed to price-sensitive passengers. First, they occur, to a greater extent, when the number of reserving seats is equal to 5, thus suggesting the presence of a sort of 'family discount'; second, they are higher for reservations made with more advance and for shorter trips, which are two conditions under which passengers are usually more elastic.

3.5. Conclusion

Taking a consumer perspective, this study has analysed the two-part tariff adopted by easyJet, composed by a fixed fee of €17 per reservation and a variable component. By using an extensive dataset of fares offered for flights during 8 March 2015 to 22 April 2015, the analysis highlights that the minimum daily unit price is usually offered for 5-seat reservations (74% of the 76,195 daily reservations), thus showing an evident 5-seat quantity discount. No significant differences in this quantity discount are observed for various numbers of seats available at the time of booking or for the number of days the reservation is booked in

[10] Further statistics on how quantity discounts vary according to destinations are available in Appendix 1.

advance of the departure date. On average, the 5-seat discount is equal to €9.48, which is 14% of the single-seat fare.

Deepening the analysis by the use of multivariate analysis, results show a significant variation in the value of the average percentage quantity discount associated with characteristics of flights and routes. In particular, the quantity discount is greater for reservations made more in advance, for flights on which a greater number of seats is available at the time of booking, and for flights departing during weekdays and in the morning. The quantity discount is lower for longer routes, for routes with larger destination airports, for routes where easyJet's market share is higher, and for routes to poorer regions.

Although the dynamic pricing literature has highlighted that the implementation of intertemporal price discrimination may enable passengers to save money by booking their flights in advance, no study has pointed out that fares are, on average, lower for (small) groups of consumers, independently from the advance-booking factor. Of particular interest in this work is that, in providing evidence of quantity discounts, no 'old theory' has been dismantled: Prices still increase as the departure date approaches and vary according to the day of the week and the hour of departure. Thus, the usual attempt of third-degree price discrimination, generally carried out by segmenting the market into high yield/business passengers and leisure passengers, still takes place, independently from the quantity-discount effect. In fact, quantity discounts are rather steady, ranging from €8 to €10, even in correspondence to the usual last-day fare surges.

However, this study does not come without limitations, which can be properly addressed in future research. First, findings may be corroborated by considering other easyJet routes, rather than only those departing from AMS, and by analysing a longer time period. Second, determining whether other airlines are implementing this type of pricing strategy could be of interest. This could enable a better understanding of the competitive dynamics of the air transportation industry. Third, the dataset could be enlarged by considering not only multiple of 5 booking volumes, but investigating other booking volumes as well (2, 3, and 4). Other directions for future research may include issues related to strategic consumers such as whether passengers' knowledge about the presence of quantity discounts could lead to different booking patterns (the “joining-together” effect) and thus a reduction in airlines’ revenues.

Chapter 4 – Multi-dimensional price elasticity of demand[11]

4.1. Introduction

Given the characteristics of the air transport industry (see Chapter 2), airlines and especially 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 (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[12] (Klophaus et al., 2012, Morandi et al., 2015), makes it even more interesting to understand the price elasticity dynamics in this sector. Indeed, the low-cost strategy has been effective to target passengers who are highly price sensitive (such as leisure ones), whereas airline hybridization is likely to mix passenger segments by targeting both price elastic and inelastic demand.

As anticipated in Chapter 3, LCCs have not implemented third-degree price discrimination by providing different travel classes. Rather, they have generally relied on intertemporal price discrimination to suit passengers' various willingness to pay (Moreno-Izquierdo et al., 2015).

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[11] This chapter aims to investigate how consumers' price elasticity of demand vary in relation to different dimensions. It is derived from the article 'Morlotti, C., Cattaneo, M., Malighetti, P., and Redondi, R. (2017). Multi-dimensional price elasticity for leisure and business destinations in the low-cost air transport market: Evidence from easyJet. *Tourism Management*, 61, 23-34.' I would like to thank my co-authors for the support received. I am responsible for all the changes in this chapter with respect to the published version. I want to express my gratitude for the comments and ideas offered by the participants at the 2016 ATRS conference in Rhodes.

[12] 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).

The recent orientation towards the business component makes it more crucial to understand different LCC passengers' price elasticities. To this extent, this chapter aims 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).

As specified in Section 2.3, it is crucial to identify demand changes in relation to price variations but 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).

In order to investigate the price elasticity of demand in the European LCC air transport industry, Internet fares for all flights on easyJet (the second European LCC in terms of passengers in the year 2015[13]) that depart from the Amsterdam Schiphol airport towards 21 European routes between March and September 2015 are examined. 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 and Guillou, 2004; Moreno-Izquierdo et al., 2015), allow new insights that complement the existing US-based evidence on passengers' price sensitivities of demand (Granados et al., 2012b). Consistent with the former literature, an instrumental variable approach is implemented 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 chapter is organised as follows. Section 3.2 describes the research design and methodology. Section 3.3 reports the results of the preliminary and empirical analyses. Section 0 summarises the conclusions and proposes directions for further research.

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

3.2. Research Design

This section describes the sample and data used for the analysis, as well as the methodology applied.

3.2.1. Sample and data

In order to measure the price elasticity of demand across different dimensions, a linear regression model is implemented, analysing the factors that influence the number of tickets sold, which represents a proxy for demand (Granados et al., 2012b). For this purpose, it is developed a unique dataset including all daily web fares for easyJet flights on 21 European routes[14] (Figure 4.1) 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.

The importance of this analysis, which is based in a European context, 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 and 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 and 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 and Royo-Vela, 2010; Williams, 2001).

The choice of easyJet as leading European low-cost carrier have several reasons. First, 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

[14] The set of routes is the same as in Chapter 3.

strong position in already served airports, like London Gatwick and Milan Malpensa, and opening important new bases, like Amsterdam Schiphol airport[15] (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 allows to identify the different price elasticities of demand for high yield/business and leisure passengers.

[15] 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.

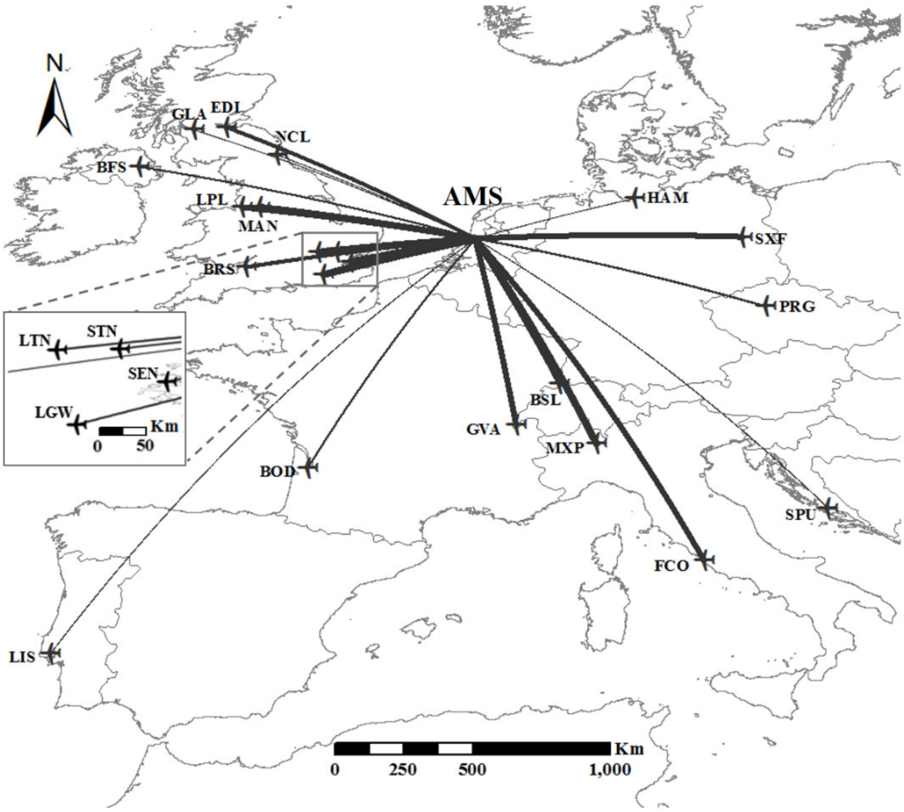

Figure 4.1 - easyJet's routes during the period March–September 2015

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

3.2.2. 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), this study attempts to solve price endogeneity by using a two-stage least squares instrumental variable approach 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)[16]. Specifically, routes are first aggregated 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,* it is computed the average price on routes *n-m* that are in the same class as route m.

The two stages of the model are as follows:

Stage 1:

$$\mathrm{P_{irdt}} = \alpha + \beta \mathrm{IV_{rdt}} + \gamma \mathrm{X_{irdt}} + \varepsilon_{\mathrm{irdt}} \tag{4.1}$$

Stage 2:

$$\mathrm{D_{irdt}} = \delta + \theta \widehat{\mathrm{P_{irdt}}} + \vartheta \mathrm{X_{irdt}} + \mathrm{u_{irdt}} \tag{4.2}$$

In the first stage, $\mathrm{P_{irdt}}$ is the price for a seat purchased by a single passenger t days in advance for flight i on route r departing on day $d;$ $\mathrm{IV_{rdt}}$ 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, $\mathrm{D_{irdt}}$ is the number of tickets sold at time t on route r, and $\widehat{\mathrm{P_{irdt}}}$ is the predicted price from the first stage. Similar to the first stage, $\mathrm{u_{irdt}}$ is the error term. In both stages, $\mathrm{X_{irdt}}$ 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.

[16] 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).

- 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).
- 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[17], 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, first the time required for each alternative (t_a) is multiplied 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, as eligible alternatives are considered 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:

  $$\left|1-\frac{(C_a * t_a)}{(C_r * t_r)}\right| < 0.20 \qquad (4.3)$$

  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.

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

After the first stage of the analysis, this study moves 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, it is estimated the price elasticity of demand at mean values across each dimension starting from the common definition of elasticity (Schiff and Becken, 2011):

$$\eta_{D,\hat{P}} = \frac{\partial D}{\partial \hat{P}} \cdot \frac{\hat{P}}{D} = \theta \cdot \frac{\hat{P}}{D} \tag{4.4}$$

where $\overline{\hat{P}}$ 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:

$$\eta_{D_k,\widehat{P_k}} = \theta \cdot \frac{\overline{\widehat{P_k}}}{\widetilde{D_k}}, \text{ with } k \in K \tag{4.5}$$

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, this analysis provides 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, this study goes 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.

Data on unit fares and tickets sold are collected 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, it is 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[18].

[18] In detail, it is first checked if 40 seats were available. If yes, it is 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), it is controlled for the fare offered for $n - 1$ seats up to the number of seats for which the price was

4.2.3. 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, 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 of 11% (€124.60) during the summer.

The routes in the 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.

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 a proxy for demand, as in Granados et al. (2012b).

3.3. Results

Preliminary and empirical results are shown in §3.3.1 and §3.3.2, where price elasticity of demand is estimated according to different characteristics, namely booking-, flight-, route-, and seasonal- dimensions.

3.3.1. Preliminary results

First, the price and demand behaviours are analysed over time. As shown in Figure 4.2, 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 (Alderighi et al., 2015; Bergantino and 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 price-inelastic consumers (Bergantino and Capozza, 2015; Dana, 1999; Salanti et al., 2012), such as consumers travelling for business purposes, and for last-minute emergencies or holidays.

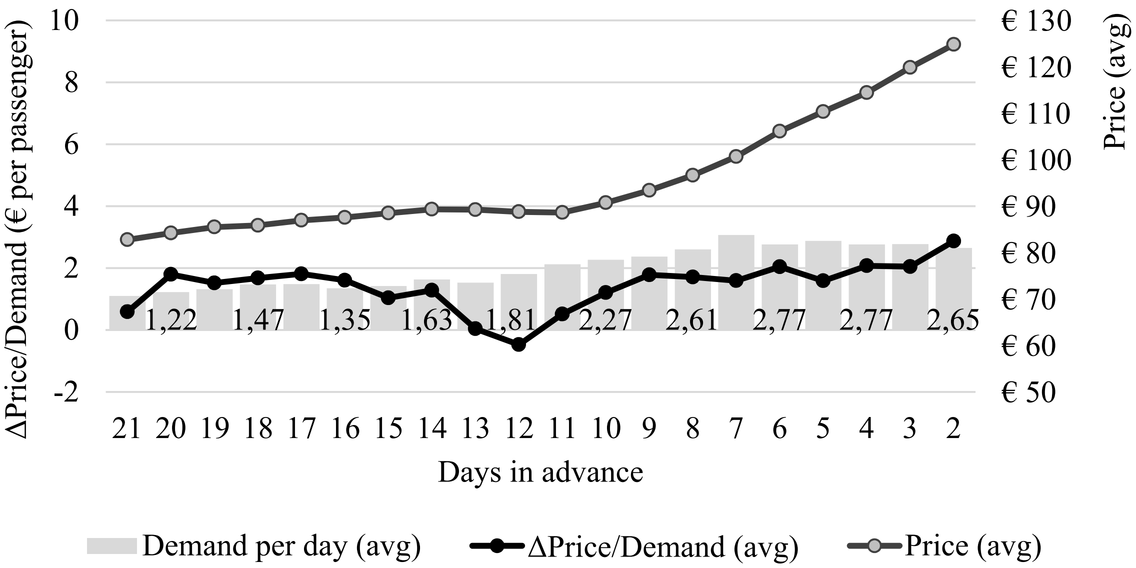

Figure 4.2 - Demand and price values by days of advance

3.3.2. Empirical results

Table 4.1 reports the results of the ordinary least squares (OLS) and the two-stage least squares (2SLS) instrumental variable regressions.[19] 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. [20] 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[21]. This evidence is consistent with the previous literature (e.g. Guevara and Ben-Akiva, 2006; Mumbower et al., 2014).

[19] The same analysis is repeated by using a three-stage least square (3SLS) regression model, which estimates the coefficients of each equation simultaneously. Results are provided in Appendix 2.
[20] Correlation matrix and fitted values with respect to price and advance are shown in Appendix 3.
[21] Multicollinearity tests dismissed the potential for problems since none of the mean variance inflation factors exceeded the typical cut-off of 10.

Table 4.1 – OLS and 2SLS regression estimates

	(1) OLS			(2) 2SLS		
	Coefficient	St. Error	P-Value	Coefficient	St. Error	P-value
Price	-0.0112***	(0.0002)	0.0000	-0.0153***	(0.0044)	0.0005
Eligible Alternatives	-0.0528***	(0.0116)	0.0000	-0.0562***	(0.0122)	0.0000
LC Dominance	0.7986***	(0.1302)	0.0000	0.7221***	(0.1537)	0.0000
Departure Hours (Evening is the ref. case)						
Morning	-0.0106	(0.0271)	0.6950	-0.0651	(0.0641)	0.3102
Lunchtime	-0.2103***	(0.0321)	0.0000	-0.2509***	(0.0540)	0.0000
Afternoon	-0.0594*	(0.0286)	0.0377	-0.0725*	(0.0319)	0.0230
Departure Days (Saturday is the ref. case)						
Sunday	0.2822***	(0.0319)	0.0000	0.4068**	(0.1378)	0.0032
Monday	0.5451***	(0.0331)	0.0000	0.5624***	(0.0385)	0.0000
Tuesday	0.8614***	(0.0407)	0.0000	0.8250***	(0.0555)	0.0000
Wednesday	0.8507***	(0.0406)	0.0000	0.8099***	(0.0588)	0.0000
Thursday	0.9063***	(0.0383)	0.0000	0.9055***	(0.0383)	0.0000
Friday	0.6002***	(0.0330)	0.0000	0.6093***	(0.0347)	0.0000
Reservation Days (Saturday is the ref. case)						
Sunday	0.1460***	(0.0271)	0.0000	0.1410***	(0.0278)	0.0000
Monday	1.5412***	(0.0324)	0.0000	1.5353***	(0.0331)	0.0000
Tuesday	1.4986***	(0.0322)	0.0000	1.4917***	(0.0331)	0.0000
Wednesday	1.5006***	(0.0327)	0.0000	1.4919***	(0.0341)	0.0000
Thursday	1.4029***	(0.0327)	0.0000	1.3954***	(0.0338)	0.0000
Friday	1.2428***	(0.0315)	0.0000	1.2411***	(0.0317)	0.0000
Month (September is the ref. case)						
March	-0.4506***	(0.0410)	0.0000	-0.5390***	(0.1031)	0.0000
April	-0.3831***	(0.0384)	0.0000	-0.3860***	(0.0385)	0.0000
May	-0.4111***	(0.0388)	0.0000	-0.4363***	(0.0472)	0.0000
June	-0.1795***	(0.0404)	0.0000	-0.2225***	(0.0607)	0.0002
July	0.1223**	(0.0414)	0.0031	0.1733*	(0.0689)	0.0119
August	-0.3314***	(0.0398)	0.0000	-0.3322***	(0.0398)	0.0000
Advance	-0.0638***	(0.0014)	0.0000	-0.0644***	(0.0015)	0.0000
Constant	2.7040***	(0.1096)	0.0000	3.2730***	(0.6187)	0.0000
Observations	66,716			66,716		
Adj.Rsquared	0.1773			-		
F-statistic	311.39			270.67		

Note: ***, **, *, and + indicate significance at the less than 0.1%, 1%, 5%, and 10% levels, respectively.

After estimating the two-stage least squares instrumental variable model, the price elasticity of demand is computed.[22] 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. These 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 (Mumbower et al. 2014 find an elasticity of -1.97 in the case of JetBlue,). The value below unity is for different reasons. First, easyJet more directly targets business passengers as compared to other LCCs by offering flexible fares and operating in primary airports (Mason, 2000; Papatheodorou and Lei, 2006). Second, the Amsterdam Schiphol airport is recognised to be an important hub for business affairs. Ultimately, easyJet is the only carrier offering flights in the majority of routes considered (16 over 21).

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

3.3.2.1. Booking dimension

The first step is to observe how the price elasticity of demand varies according to the number of days in advance that the ticket is booked. Figure 4.3 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 high yield passengers are likely to respond differently to price changes (Brons et al., 2002; Oum et al., 1992). It is indeed well known that, for example, business passengers are less price sensitive than leisure passengers

[22] See Appendix 5 for price elasticity results without correcting for price endogeneity.

(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.[23] This result is analogous to that of Mumbower et al. (2014): the elasticity increases as the departure day moves further away.

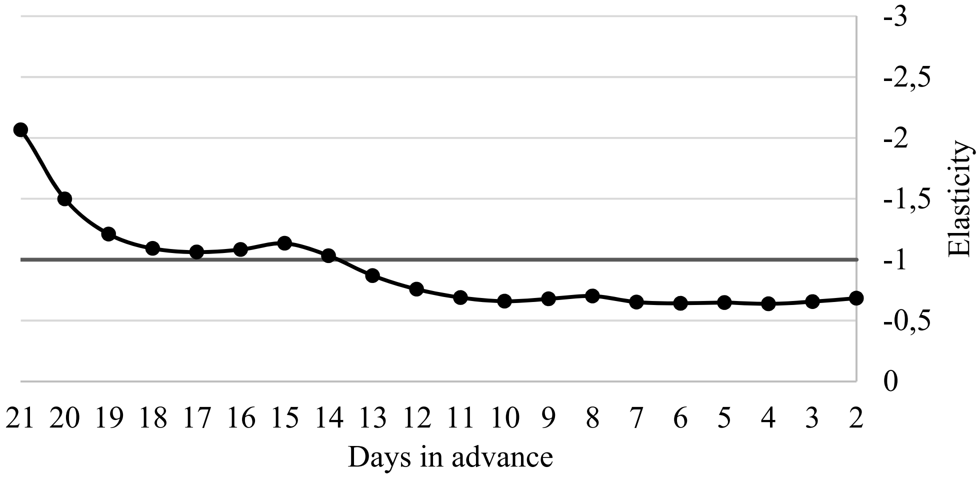

Figure 4.3 - Price elasticity values by days in advance
Notes: All elasticity values are significant at the <0.1% level
The ANOVA F-statistic (43) is 26.76, significant at the <0.1% level

Similarly, price elasticity changes according to the booking day of the week are computed. As shown in Table 4.2, 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

[23] Market segmentation can be analysed from different perspectives, such as, for example, price- and time- sensitivity, or behavioural and socio-demographic variables (Harrison et al., 2015; Mason, 2002; Swan, 2002; Teichert et al., 2008). By focusing on price sensitivity, literature in the air transport industry usually identifies two main segments, i.e., passengers travelling for business and for leisure purposes. Certainty, business passengers are just one kind of travellers who can be defined as inelastic. For example, scholars recognise as low-price sensitive passengers also highly income leisure travellers, school vacation demand, lastminute consumers, and passengers flying for emergencies (Harrison et al., 2015; Swan, 2002; Teichert et al., 2008).
Furthermore, evidence shows that a portion of business passengers is tending to choose their flights in relation to prices (Mason, 2002). For the sake of simplicity, in this thesis inelastic passengers are defined as high-yield passengers, comprehending that part of business passengers who is not sensitive to prices.

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 and 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).

Table 4.2 – 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 <0.1% level
**** indicates statistical significance at the 0.1% level*

3.3.2.2. *Flight dimension*

The price elasticity is also found to vary according to the departure day. As shown in Table 4.3, 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 high yield/business and leisure passengers and to suit their various willingness to pay (Salanti et al. 2012).

Table 4.3 – 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 <0.1% level	
**** indicates statistical significance at the 0.1% 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 4.3). This result highlights that flights early in the morning are more business oriented (Alderighi et al., 2016; Borenstein and Netz, 1999).

3.3.2.3. Route dimension

Figure 4.4 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). Results are also consistent with the findings of Salanti et al. (2012), who develop a 'leisure index' to disentangle business and leisure routes.[24]

Computing the same index, it is found 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 the analysis showing that the level of the price elasticity can provide information on the different types of routes (business- or leisure-oriented).

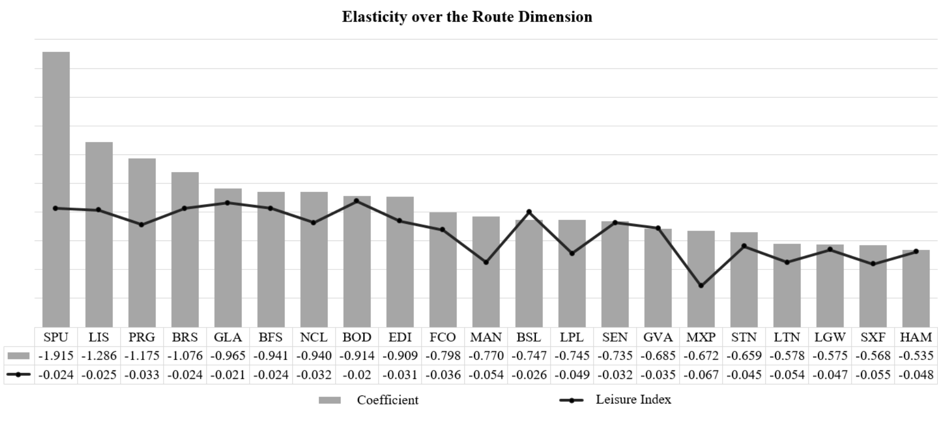

Figure 4.4 – Price elasticity value per route and the relative leisure index
Notes: All elasticity values are significant at the <0.1% level
The ANOVA F-statistic (20) is 73.75, significant at the <0.1% level

[24] See further details on the leisure index in Appendix 4.

3.3.2.4. 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 4.4), 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.

Given the existing variations in the price elasticity of demand across different dimensions (booking, flight, and route) this study 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 4.5 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 an 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%). In terms of route characteristics, destinations where easyJet is the only low-cost carrier offering flights present a 10% lower price elasticity in spring with respect to summer, while routes suffering from competition have a quasi-stable price elasticity, equal to -0.797 in spring and -0.790 in summer.

Table 4.4 – 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 <0.1% level
**** indicates statistical significance at the 0.1% level*
[a]Summer starts on 21 June

When looking in details of different routes in different seasons, the elasticity values in Table 4.6 help in clarifying which routes can be considered as more business or more leisure oriented throughout the seasons. In particular, from the previous Figure 4.4, Bristol (BRS), Lisbon (LIS), Prague (PRG), and Split (SPU) are the most leisure-oriented routes in the sample. However, by looking at Table 4.6, only Bristol (BRS), and Lisbon (LIS) have elasticities greater than one during both the spring and summer months. The other destinations vary according to the season. Specifically, Bordeaux (BOD) and Prague (PRG) are characterized by highly price elastic passengers only during the springtime, whereas Belfast (BFS), Edinburgh (EDI), Glasgow (GLA), and Split (SPU) are characterized that way only 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, variations in the number of flights per route in the two different seasons are explored. Usually, the number of flights decreases by 18% during the summer.

Table 4.5 – Price elasticity values per season, days of advance, booking day, departure day, and 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***	

Note: All elasticity values are significant at the <0.1% level
**** indicates statistical significance at the 0.1% level*

Table 4.6 – Price elasticity values per season and route, 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***		
LC Dominance					
<100%	-0.797	-0.790	2,113	1,669	-21%
100%	-0.666	-0.748	1,845	1,584	-14%
ANOVA F-Statistic (2)			125.60***		

Notes: All elasticity values are significant at the <0.1% level
**** indicates statistical significance at the 0.1% level*
[a] Flight variations are computed as the percentage difference between the number of summer and spring flights

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.

3.4. 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, this study relies on an extensive dataset of reservations and fares offered online by easyJet for flights during the period 8 March–23 September 2015.

Results highlight that the overall price elasticity of demand is equal to -0.753, suggesting that easyJet targets a high proportion of low-price sensitive passengers. By deepening the analysis and looking at the booking, flight, route, and seasonal dimensions, results show 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. Findings are also confirmed when controlling for different seasons.

These results shed light on the different price sensitivities of leisure and high yield/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 and 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.

By focusing on the European context, this work contributes to the literature evidencing how price elasticity of demand varies according to booking, flight, route and seasonal dimensions. These study's estimates on price elasticity have managerial policy implications for different stakeholders, namely airlines, passengers, and tourism managers. On the supply side, 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 if airlines 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, 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 and 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. 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, this 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 and 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 and 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 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 better clarify the booking preferences of high yield/business and leisure travellers.

Chapter 5 – The role of price volatility in consumers' price sensitivity[25]

5.1. Introduction

It is acknowledged that economic, marketing, and operational research studies aim to properly estimate and understand how demand responds, among all, to prices and their variations (Muth, 1961; Shepherd and Shepherd, 2003; Whitin, 1955). In general terms, as price increases, demand tends to decrease, as shown in Chapter 4. In practice, however, the actual relationship between price and demand is more intricate as it may depend on the history of prices to which customers were exposed to: as prices fluctuate over time, consumers' perceptions and expectations change, thereby affecting their price sensitivity. Stated differently, being exposed to volatile prices may influence consumers' purchasing decisions and how they respond to price changes.

Fluctuating prices are prevalent in the context of revenue-managed goods. In the classical revenue management setting, a fixed number of items with a known expiration date are at the disposal of the firm to be sold to a segmentable stream of consumers who arrive sequentially over time (Gallego and van Ryzin, 1994; Feng and Gallego, 2000). The challenge faced by the profit-maximizing firm is to determine the proper prices to offer to the different consumers over the finite time horizon (Talluri and var Ryzin, 2004). Numerous industries encounter such an environment, among which the airline industry was the avant-garde in adopting and advancing the use of revenue management practices. Evidence shows that use

[25] This chapter aims to explore the extent to which the effects of revenue management applied strategies may impact on consumers' price sensitivities. It is derived from the article 'Morlotti, C., Mantin, B., Malighetti, P., and Redondi, R. (2018). Does Price Volatility Influence Demand of Revenue Managed Goods?', currently under review in Management Science. I would like to thank my co-authors for the support received. I am responsible for all the changes in this chapter with respect to the last version presented at the 2018 ATRS conference in Seoul. I want to express my gratitude for the comments and ideas offered by the participants at the 2018 ATRS conference in Rhodes and the 2017 AiIG Annual Conference in Bari.

of revenue management allows airlines to increase both their load factors and revenues up to 7.3% (Smith et al., 1992; Zhao and Zheng, 2000).

The common implementation of revenue management results with the design of fare classes and the estimation of the demand for each of these fare classes. Subsequently, these fare classes are opened and closed as demand is realized over time whilst accounting for deviations from the expected selling path (See Section 2.1 and Section 5.5. for additional details on revenue management theory and formulation, respectively). The resulting prices may exhibit varying patterns of price volatility (e.g., McGill and van Ryzin, 1999; Gillen and Mantin, 2009). The rate at which these realized prices change is becoming increasingly faster and is following more sophisticated mechanisms (Brynjolfsson and Smith, 2003), thanks also to the increasing engagement in online purchasing, as the web enables faster and almost costless updating of fare classes and, hence, posted prices.

It is well established that consumers respond to fluctuating prices (e.g., Murthi et al., 2007). In the context of consumer-packaged goods, the marketing literature highlights the following strong relation between consumers' purchasing behaviour and price volatility: with increased price fluctuations consumers' uncertainties increase, thereby decreasing their price sensitivity (Janiszweski and Lichtenstein; 1991; Winer, 1986; Murthi et al., 2007). In this chapter it is explored whether these insights can be generalized and hold for revenue-managed goods where consumers expect prices to fluctuate and follow somewhat predictable price trajectories over time. To this extent, it is measured how demand changes with respect to price and different levels of price volatility by means of price elasticity of demand.

Demand price elasticity is the most common measure summarizing how consumers respond to price changes (e.g., Andreyeva et al., 2010; Tellis et al., 1988). Practically, it explains the percentage change in purchased quantity with respect to a 1% change in price, and it can be influenced by several factors, such as household income, availability of substitute products and more generally consumers' preferences and perceptions. Although the definition of price elasticity is fairly simple, significantly different price elasticity estimates can be found for the same goods according to different dimensions. For instance, measuring price elasticity at different points in time along the life-cycle of a product leads to extremely different results (e.g., Parsons, 1975), as it basically reflects consumers' willingness to pay. In the case of revenue managed goods, such as air transport, evidence demonstrates that price elasticity varies according to different levels of route-, season-, flight-, and booking- characteristics (e.g., Mumbower et al., 2014; Smyth and Pearce, 2008).

Given the popularity of revenue management and the realization that consumers respond to fluctuating prices, it is rather surprising that the revenue management literature largely ignores this behaviour and merely treats demand as static (i.e., does not respond to temporal changes in prices[26]) while, at the same time, the price elasticity literature largely ignores the underlying price patterns of revenue-managed goods. Could it be that the earlier findings on consumers' responses to volatile prices are driven by the fact that these studies were carried out in the context of consumer-packaged goods, which may be subject to certain considerations (such as stockpiling or delayed consumption)? Do revenue-managed goods exhibit a different pattern of demand response to fluctuating prices? To some degree, the "predictable" path of prices—as consumers learn to expect such changing prices and trajectories towards the expiration date of the good—could play a factor in their own responses to these changes (Mantin and Rubin, 2016).[27]

The study takes as leading example to explore the impact of price volatility in the context of revenue management the proto-typical revenue management industry: air transport. Whilst an extensive economics literature explores various aspects of airline pricing (such as the link between competition and fare dispersion, see, e.g., Gerardi and Shapiro, 2009, or the pricing decisions of incumbent carriers under the threat of entry from low-cost competitors, see, e.g. Goolsbee and Syverson, 2008), this analysis' interest is in the operational aspect of pricing. Accordingly, by using data collected from the airline industry, the purpose is to quantify

[26] Some aspects of the temporal pricing effects have been captured such as the buy-up and buy-down effects (Cooper et al., 2006), and the more recent applications with strategic consumers with potential upgrades (Yılmaz et al., 2017). However, these still abstract away from the notion of changing consumer behaviour due to the exposure to volatile prices.

[27] Consumers increasingly have access to fare prediction tools which provide them with access to past fare histories. For instance, in the context of airfares, popular fare prediction tools include, among others, *Kayak, AirHint* and *Hopper*. The latter is only available as a mobile application. *Farecast*, probably the first and the most prominent tool for a while, closed in 2014, after being purchased by Microsoft in 2008.

consumers' responses to prices and fares fluctuations when considering the purchase of revenue managed goods. Specifically, recognizing that consumers may observe prices over time, the goal is to quantify the impact of price fluctuations on demand, assess their price elasticity for different degrees of price volatility, and ultimately integrate this behaviour back into revenue management practices.

This study's methodological approach consists of several steps. In the first step, it is considered a price volatility measurement that embeds the inherent price trajectories of revenue managed goods. This price volatility construct relies on the existing definition from the marketing literature which captures human perceptions of fluctuating prices (e.g., Murthi et al., 2007). However, the measurement incorporates two adjustments. First, recognizing the vast differences in price levels across origin-destination markets (unlike consumer-packaged goods), relative price changes rather than absolute price changes are considered (Gillen and Mantin, 2009). Second, given the acknowledged inter-temporal price discrimination characterizing the airline pricing strategy (e.g., Bergantino and Capozza, 2015) mainly due to the closure of lower fare classes as departure day approaches, it is included in the price volatility measure the airfare variations with respect to the predicted price movements as the departure nears, by utilizing the pricing formulation from Malighetti et al. (2009). Thus, the price volatility measure quantifies the relative deviations from predicted price paths.[28]

In the second step, the empirical analysis is carried out. By means of a two-stage least squared regressions, the analysis explores the determinants of air transport demand, capturing flight- and route- features, as well as price characteristics, i.e., price level, the extent to which airfares drop with respect to the previous day, and price volatility. While strategic consumer behaviour is not explicitly captured at this stage, the variable that measures the price drop from one day to the next embeds some of this information. Being positive and significant, this variable suggests the presence of strategic waiting among consumers. Importantly, price volatility emerges as a significant variable bearing a negative impact on demand, indicating that price fluctuations tend to be negatively associated with consumers' purchasing

[28] Furthermore, to account for seasonality (as in Morlotti et al., 2017), this measure is calculated on a monthly basis.

propensity. This is an important insight that complements the pertinent literature. Indeed, while marketing literature suggests that price volatility leads to higher prices paid with no impact on the volume sold, this paper shed light on the fact that price volatility impacts also on volume. In these terms, the extent to which generating price volatility is beneficial for the seller has not to be taken for granted. The mechanism resulting with this relationship is further revealed in the next step.

In the third step, it is estimated price elasticity of demand and how it varies according to the different levels of price volatility. Specifically, using the estimation results from the second step, it is computed the price elasticity of demand according to different levels of price volatility. Namely, by categorizing markets into deciles of price volatility, it is possible to assess the magnitude impact of different level of price volatility. Results show a decreasing magnitude of price elasticity (in absolute values) in the degree of price volatility. This is in line with the marketing literature suggesting that an increased price variability is associated with more inelastic demand. Hence, the analysis lends support to the notion that with volatile prices consumers—whose demand become less elastic—end up paying higher fares for the flights, but given the classic price-demand relationship, also end up buying less, and hence the negative linkage between price volatility and demand (from the second step).

In the fourth step, it is demonstrated how firms may use these insights to support them in their (re-)design of revenue management practices to potentially influence demand and increase their revenues. To that end, it is considered the typical revenue management model, Expected Marginal Seat Revenue or EMSR (Belobaba, 1989), and following the illustration of Anderson and Wilson (2003), it is introduced—in a rather stylized manner—the impact of price volatility. Results show how accounting for the effects of price volatility on demand may increase profitability by up to 5% in the numerical examples. Lastly, it is recognized the detrimental effect of the presence of strategic consumers who seek to optimally time their purchase along the pricing path of a product (e.g., Cachon and Swinney, 2009). Evidence suggests that a considerable number of consumers exhibit such behaviour, enhanced by the presence of web fare prediction tools which often provide statistical inference on the direction of future price movements thereby supporting strategic consumer behaviour (Mantin and

Rubin, 2016). Accordingly, the numerical EMSR simulation is revised to further include a varying proportion of strategic consumers.[29] This gives rise to a delicate trade-off suggesting ranges where inducing price volatility can be beneficial for firms and ranges where it has to be more cautious due to the presence of strategic consumers.

The remainder of this chapter is organised as follows. Section 5.2 presents the employed measures of price volatility. Section 5.3 describes the research design and methodology. Section 5.4 reports the results of the empirical analyses. Section 5.5 proposes a simplified methodology highlighting the integration of price volatility into the conventional revenue management procedures. Section 5.6 summarises the results and offers directions for further research.

5.2. Measuring price volatility

Price volatility has a significant impact on consumers' behaviour (see, e.g., Murthi et al., 2007). For instance, consumers who are exposed to price fluctuations become less price sensitive (e.g., Janiszweski and Lichtenstein; 1991). The reasons underpinning this decrease in price sensitivity rely on the uncertainty consumers faced when exposed to price variations (e.g., Winer, 1989). Higher levels of price volatility have also been found to increase the ranges of acceptable prices (Dickson and Sawyer, 1990; Winer, 1986), as well as the value of the reference price, defined as the "right" price perceived by consumers (Rao and Sieben, 1992; Kalyanaram and Little, 1994). Murthi et al. (2007) further corroborate former literature showing that price volatility increases the level and the range of reference prices, thus decreasing consumers' price sensitivity as they allocate more weight to price decreases compared with price increases. This consequently distorts the difference between reference and actual price.

The marketing literature, however, has derived all these insights using the consumer-packaged goods (CPG) category. Certain features associated with CPGs (such as the

[29] There is no agreement as to the actual proportion of strategic consumers in the population. For example, according to Li et al. (2014), it ranges between 5% and 20% whereas Osadchiy and Bendoly (2015) estimates it to reach 77%.

storability, expiration, and availability of comparable products) raise concerns regarding the generalizability of the insights to revenue managed goods. To facilitate understanding of how consumers may react to volatile price in the context of revenue-managed goods, it is important to properly capture the degree of price volatility in such markets.

The traditional marketing approach to measure price volatility "captures the price patterns by giving different weights to recent relative to more distant changes in prices" (Han et al., 2001), in a fashion that is more consistent with human behaviour. Specifically, price volatility is formulated as follows:

$$\mathrm{PVOL}_{i,t} = \theta \mathrm{PVOL}_{i,t\text{-}1} + (1\text{-}\theta)\left(\mathrm{P}_{i,t}\text{-}\mathrm{P}_{i,t\text{-}1}\right)^2 \quad \text{with } \mathrm{PVOL}_1 = 0, \tag{5.1}$$

where $\mathrm{PVOL}_{i,t}$ and $\mathrm{P}_{i,t}$represent the price volatility and the price, respectively, of product i in period t; while θ is a smoothing constant indicating the weight assigned to past price changes with respect to the most recent variation of prices.

Within the same product category, different products are expected to bear a comparable price. However, in airline markets price may differ dramatically from one market (defined as origin-destination airport pair) to another. This can be an outcome of the distance, the competition intensity in the market, or simply by the market's leisure or business orientation (e.g., Salanti et al., 2012). To that end, Gillen and Mantin (2009) have considered a normalized measure of price volatility (PVOLN_{it}), whereby the daily percentage change in prices is captured rather than the absolute price fluctuation. Their normalized price volatility is computed as follows:

$$\mathrm{PVOLN}_{i,t} = \theta \mathrm{PVOLN}_{i,t+1} + (1\text{-}\theta)\left(\frac{\mathrm{P}_{i,t}\text{-}\mathrm{P}_{i,t+1}}{\mathrm{P}_{i,t+1}}\right)^2, \qquad \text{with } \mathrm{PVOLN}_{i,T} = 0, \tag{5.2}$$

where $\mathrm{PVOLN}_{i,t}$is the normalized price volatility. Note that time subscript is now in reverse order. That is, given the expiration (the departure date), in this formulation, t indicates the advance time and T is the first day on which observations starts with 1 being the final day before the product expires.

To refine the price volatility measure, note that the realized prices essentially follow the implementation of quantity-based revenue management (e.g., Belobaba, 1989; Talluri and van Ryzin, 2004; van Ryzin and McGill, 2000; Weatherford and Bodily, 1992). In that case, prices are set in advance and products belong to different fare classes while sellers dynamically adjust the quantity of units in each of the classes in response to changes in the market conditions (Talluri and van Ryzin, 2004).[30] Evidence suggest that airfares vary dynamically according to factors such as the number of remaining seats (e.g., Alderighi et al., 2015), the remaining days to departure (e.g., Malighetti et al., 2009), and other market, flight, and booking characteristics (Salanti et al., 2012). All in all, this may lead to high dynamicity of the fares available to consumers (Boyd and Bilegan, 2003), inducing price volatility. Having that said, airfares still follow some predictable price trajectories. Following the formulation of Malighetti et al. (2009) while recognising that airlines' dynamic pricing strategies vary on different dimensions, the study aggregates and distinguishes between different flight numbers offered on different months (i.e., accounting for seasonality). Thus, the price path of flight i offered in month m on route r, $\widetilde{\mathrm{P}}_{\mathrm{irt}}$, is formulated as follows:

$$\widetilde{\mathrm{P}}_{\mathrm{irmt}} = \mu_{\mathrm{imr}} + \frac{1}{\alpha_{\mathrm{imr}}(1+\beta_{\mathrm{imr}}\cdot t+\gamma_{\mathrm{imr}}\cdot t^2)} \tag{5.3}$$

with μ_{ir}being the minimum price level of a flight i offered in month m on route r, while α, β, and γ determine the influence of days of advance (t) on airfares. In details, α reflects the level of prices towards the departure date, β represents the speed of increase in airfares, and γ adjusts the trend curvature.

Accordingly, it is employed a new measure of price volatility, which adopts the PVOLN definition from Gillen and Mantin (2009) while explicitly capturing price fluctuations from predictable price moves over time, as in Mantin and Rubin (2018). The new measure of price volatility, therefore, becomes:

$$\mathrm{PVNAP}_{\mathrm{i,t}} = \mathrm{PVNAP}_{\mathrm{i,t+1}} + (1\text{-}\theta)\left(\frac{\frac{\mathrm{P_{i,t}}}{\widetilde{\mathrm{P}}_{\mathrm{i,t}}}}{\frac{\mathrm{P_{i,t+1}}}{\widetilde{\mathrm{P}}_{\mathrm{i,t+1}}}}\text{-}1\right)^2 \text{,with } \mathrm{PVNAP}_{\mathrm{i,T}} = 0 \tag{5.4}$$

[30] In an alternative approach, a firm can practice dynamic pricing (e.g., Gallego and van Ryzin, 1994; Elmaghraby and Keskinocak, 2003; Talluri and van Ryzin, 2004; Zhao and Zheng, 2000). This is often exercised by offering a single product while dynamically adjusting the fare of this product based on capacity and demand (Talluri and van Ryzin, 2004). The implementation of this strategy may still result with volatile prices.

With respect to PVOLN, PVNAP is expected to be lower in absolute values, as it represents the relative changes in the ratio between offered and predicted prices.

5.3. Data and Estimation Methodology

In this section data collection used for the empirical analysis is described (§5.3.1). It is then outlined how a two-stage least square regression is carried out to understand the determinants of demand, controlling for the endogeneity existing between price and demand (§5.3.2). This allows to determine the degrees of price volatility characterizing a market in a certain day of advance and with respect to the flight characteristics (e.g., month, day, and hour of departure). Lastly, it is computed the price elasticity of demand at mean prices for each decile of price volatility (See Section 3.2.2 for further details on the computation of price elasticity)[31].

5.3.1. Data

In order to estimate how price volatility may influence passengers' price elasticity of demand, both air ticket prices and the number of daily purchases are needed. While such data is not publicly available, this paper relies on an innovative data collection approach to ensure both pricing and sales data. To gather pricing data, fares offered by a major European airline carrier[32] on its website are downloaded on a daily basis spanning over the final 45 days prior to departure on 21 European destinations departing from Amsterdam Schiphol airport for all

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[31] In this case, k stands for the deciles of price volatility. As the average value does not properly explore the extent to which price volatility influences consumers' price elasticity (e.g., Chandra and Lederman, 2016), it is evaluated the variation in $\eta_{D,\hat{P}}$ over the different levels of price volatility, represented by decile k of volatility ($PVNAP$). Accordingly, Equation 4.4 becomes $\eta_{D_k,\widehat{P_k}} = \varphi \cdot \frac{\overline{\widehat{P_k}}}{\widetilde{D_k}}$, with $k = 1, \dots, 10$, where $\overline{\widehat{P_k}}$ and $\widetilde{D_k}$ are the overall average of predicted prices and the average of predicted value of the demand (computed as in Equation 5.5), respectively, estimated for each decile.

[32] Specifically, data from easyJet, the fifth largest European carrier by number of passengers (about 70m as of 2015), is collected. Although easyJet is regarded a low-cost carrier (LCC), which are commonly recognised to implement dynamic pricing strategies, Alderighi et al. (2017) provide evidence that the pricing of a leading LCC actually follows a price-bucket strategy and as such its airfares are set to reflect the different classes, replicating the traditional airlines' revenue management practices.

flights taking place between 8 March, 2015, and 23 September, 2015.[33] Overall, airfares are collected for 7,211 flights, with a total of 319,029 records.

Table 5.1 - Descriptive statistics of the fares per each destination, sorted by fare

Destination	Mean	Std. Dev.	Min	Max
SPU	130.999	64.594	42.990	430.990
LIS	128.896	52.432	43.990	369.990
PRG	119.725	31.736	44.990	308.990
BRS	114.751	36.580	36.990	288.990
FCO	104.592	34.721	37.990	308.990
GLA	99.221	35.636	24.990	253.990
MXP	96.922	42.537	27.990	492.990
EDI	96.810	37.656	34.990	369.990
MAN	93.343	36.942	29.990	337.990
LPL	90.098	35.395	28.990	367.990
BFS	89.975	33.227	24.990	271.990
SXF	87.068	31.018	30.990	492.990
NCL	86.643	30.480	34.990	205.990
BOD	82.812	36.421	29.990	241.990
LGW	80.795	36.630	31.990	288.990
BSL	79.538	37.022	26.990	308.990
STN	77.702	34.881	33.990	269.990
LTN	76.136	34.364	31.990	339.990
GVA	75.916	40.154	26.990	337.990
SEN	67.903	30.768	28.990	234.990
HAM	43.527	20.070	24.990	202.990

The resulting pricing sample is rather heterogenous as can be observed from Table 5.1 and Figure 5.1. For instance, the mean daily prices vary from €44 for the Hamburg market to €131 for the Split market, with an even greater variation in the price ranges recorded for the various markets. Further, differences in the progression of fares over time and in price ranges are observed, for instance, in the Hamburg market, price increase steadily with minimal change in the spread of fares, whereas in the Lisbon and Split markets, the spread is

[33] The Amsterdam Schiphol airport is the focus of this study. The main base of easyJet is London Gatwick, followed by Genève, Milan Malpensa and London Luton. In 2015, Amsterdam was positioned at the fifth place in terms of offered seats (2.5 million).

dramatically wider, and in the Berlin market, it is possible to notice a remarkable fare increase during the final 10 days.

Despite the high heterogeneity in price levels, Figure 5.1 shows a generally increasing trend of airfares as departure day approaches. This corroborates the believes that prices can be predictable over time, thus validating the use of PVNAP as a proper measure of price volatility. To develop final estimates of price volatility accounting for predictability of airfares, it is computed $\widetilde{\mathrm{P}}_{\mathrm{irmt}}$ in the sample, by fitting the nonlinear function in Equation 5.3) for all the groups of flights according to the market served, the days in advance, as well as the month, day, and hour of departure, for a total of 2,101 combinations. Figure 5.2 shows the trend of PVNAP over days of advance. Differently from price levels (Figure 5.1), price volatility presents similar values across markets. Even if by construction it increases over time, as $\mathrm{PVNAP}_{\mathrm{irdT}} = 0$, some markets (Lisbon and Split) can be identified as more volatiles than others (Hamburg and Berlin), as price volatility result register more jumps as departure day approaches.

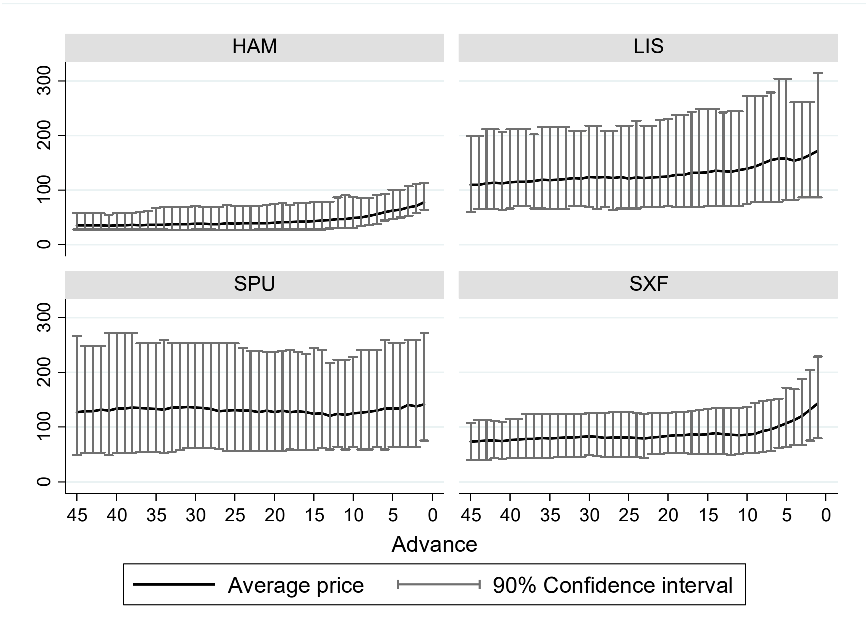

Figure 5.1 – Average fares over 45 days to departure with the respective 90% confidence intervals from Amsterdam to Hamburg (HAM), Lisbon (LIS), Split (SPU), and Berlin (SXF)

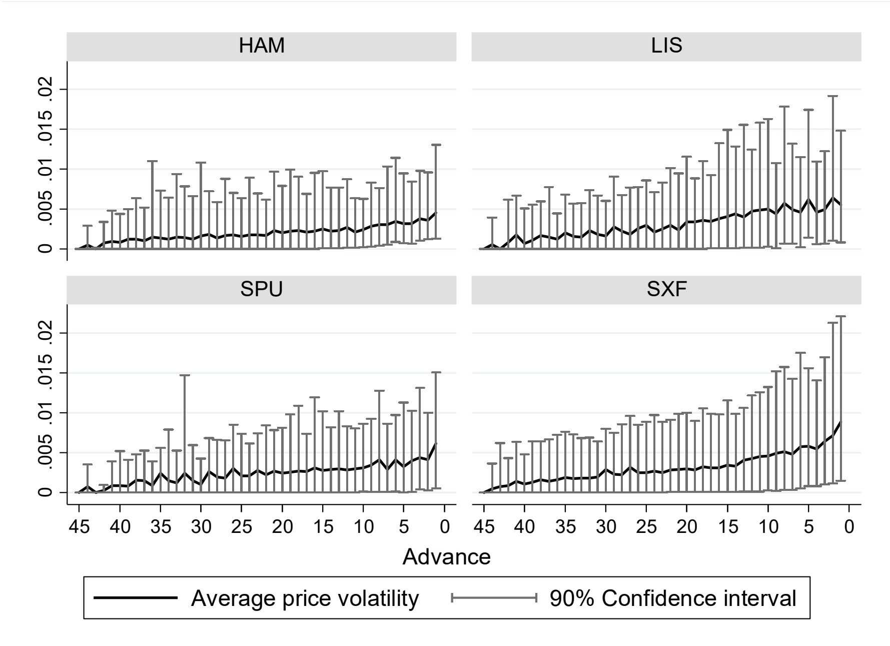

Figure 5.2 - Average PVNAP *with* $\theta = 0.8$ *over days of advance for AMS-HAM, AMS-LIS, AMS-SPU, and AMS-SXF*

While daily sales are not directly available, a procedure is implemented to compute the number of tickets sold, which is normally used in literature as a valid proxy of demand (Granados et al., 2012b; Morlotti et al., 2017). Specifically, as in Morlotti et al. (2017), it is 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.[34]

The proxy of demand also exhibits considerable variation across the different markets. For instance, the average remaining seats illustrated in Figure 5.3, suggests that in the Hamburg (HAM) market starts experiencing less than 40 seats available on the 12th day prior to departure, whereas the Split (SPU) market registers a different pattern with capacity cropping below 40 already around five weeks before departure. Table 5.2 shows descriptive statistics

[34] This reduces the number of observations in the data. From the overall sample of 319,029 records, only in 66,716 cases a number of available seats lower than 40 is registered. After data preparation, the sample is composed by 58,354 observations.

on the number of days in advance at which a flight has less than 40 seats available. The average value ranges from 10 days in case of London Gatwick (LGW) and 35 days in case of Split. Additionally, a total of 28 flights (of which 7 on the AMS-STN route, and 3 for AMS-BOD, AMS-BSL, AMS-GVA, and AMS-LGW markets) over 7,211 have more than 40 seats available on the day of departure.

Table 5.2 – Day of advance in which the number of available seats become less than 40

Destination	Mean	St. Dev.	Min	Max
SPU	35.222	9.829	13	45
NCL	21.872	4.841	13	27
GLA	20.622	4.602	7	27
BOD	20.416	8.039	0	40
LIS	20.158	8.839	3	26
PRG	19.520	7.505	10	35
BFS	18.804	6.667	5	32
BRS	18.723	7.694	4	35
EDI	18.066	5.597	0	34
SEN	18.015	6.279	0	32
BSL	17.091	8.550	0	34
FCO	14.653	3.891	0	23
MAN	14.528	6.499	0	29
GVA	14.217	5.300	0	26
LPL	13.445	2.889	0	18
HAM	12.023	6.166	0	21
STN	11.634	6.216	0	31
LTN	11.483	6.626	0	27
MXP	11.440	7.481	2	31
SXF	10.974	4.204	1	22
LGW	10.409	4.864	0	28

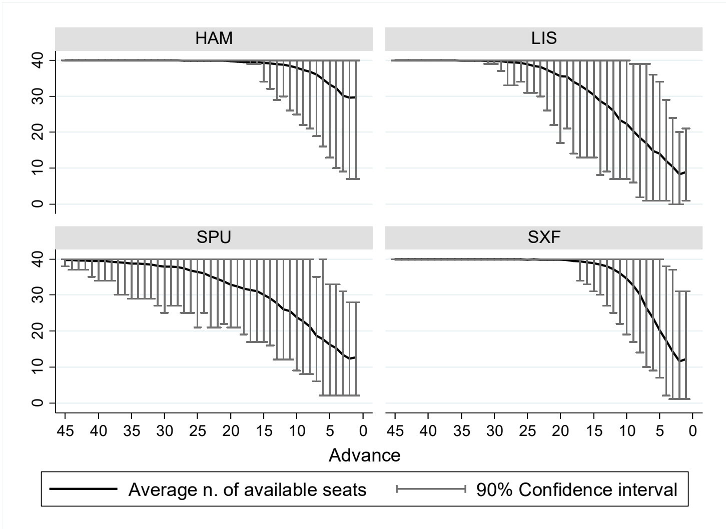

Figure 5.3 – Average observed remaining seat capacity over 45 days to departure with the respective 90% confidence intervals for AMS-HAM, AMS-LIS, AMS-SPU, and AMS-SXF. Note: 40 available seats is the maximum aircraft capacity observed

5.3.2. The determinants of demand

To measure consumers' price sensitivity with respect to price volatility, a linear regression model, identifying the factors that influence demand, is implemented where also the estimates of price volatility are included. Afterwards, the passengers' price elasticity of demand is shown, according to the level of experienced price volatility.

When investigating the relationship between price and demand, a reverse causality concern may arise, as the level of demand is affected by prices and, at the same time, demand is recognised as one of the main factors determining airfare levels (e.g., Gerardi and Shapiro, 2009). To address this potential endogeneity, a two-stage least square (2SLS) instrumental variable method is implemented. Consistent with recent studies (Mumbower et al., 2014; Morlotti et al., 2017), this analysis employs the airline's average prices in similar markets as an instrument. Following Salanti et al. (2012), similar markets are defined according to their leisure or business orientation, relying on the leisure index.[35] In the sample, leisure index

[35] See Appendix 4 for further details on the leisure index.

ranges from -0.067 (MXP) to -0.024 (SPU), thus suggesting the business-orientation of the Amsterdam-Milan route and the leisure-orientation for the Amsterdam-Split route. To categorize routes according to their levels of leisure-orientation, four categorical variables are generated according to the quartiles of the leisure index, with category 1 (resp., 4) including routes with the lowest (resp., highest) values of the leisure index (namely, the first (resp., fourth) quartile of the sample) reflecting the most business (respectively, leisure) oriented markets. After identifying the different leisure levels, for each route m, it is computed the average price on routes $\mathrm{n\text{-}m}$ that are in the same quartile of route m. The average price of the routes $\mathrm{n\text{-}m}$, computed t days in advance represents the instrumental variable for the price on route n on the date d during the $\mathrm{t^{th}}$ day before departure ($\mathrm{IV_{ndt}}$). [36]

Demand estimation is as follows:

$$\mathrm{D_{irdt}} = \delta + \varphi\widehat{\mathrm{P}}_{\mathrm{irdt}} + \rho\mathrm{Y_{irdt}} + \vartheta\mathrm{X_{irdt}} + \omega\mathrm{Z_r} + \mathrm{u_{irdt}} + \upsilon_{\mathrm{r}} \qquad (5.5)$$

where $\mathrm{D_{irdt}}$ is the number of tickets sold t days in advance for flight i on route r departing on date d, $\mathrm{X_{irdt}}$, $\mathrm{Z_r}$, and $\mathrm{Y_{irdt}}$ are vectors representing a set of independent variables, $\mathrm{u_{irdt}}$and υ_{r} are the flight- and route-related error terms, and $\widehat{\mathrm{P}}_{\mathrm{irdt}}$ is the predicted price corrected from price endogeneity, derived from:

$$\mathrm{P_{irdt}} = \alpha + \beta\mathrm{IV_{rdt}} + \gamma\mathrm{X_{irdt}} + \partial\mathrm{Z_r} + \varepsilon_{\mathrm{irdt}} + \xi_{\mathrm{r}} \qquad (5.6)$$

where $\mathrm{P_{irdt}}$ is the posted fare, $\mathrm{IV_{irdt}}$ is the selected instrumental variable, and $\varepsilon_{\mathrm{irdt}}$ and ξ_{r} are flight- and route-related error terms, respectively. The $\mathrm{X_{irdt}}$ vector is composed of flight-characteristics. Specifically, *Advance,* representing the number of days to departure (1-45) at which a ticket is bought; *Booking Weekdays* and *Departure Weekdays* are dummy variables equal to 1 when the booking and departure date is during weekdays (from Mondays to Thursdays), and 0 otherwise (from Fridays to Sundays); *Peak Hours* is a dummy variable equal to 1 when the departure hour is between 6 a.m. to 9 a.m. and from 5 p.m. to 9 p.m., 0

[36] To corroborate the results, the same analyses is conducted by considering as instrumental variable the average prices on similar routes classified according to the length of haul, as in Morlotti et al. (2017). Outcome results are coherent with the used instrument and show the same relationship among the studied variables (see Appendix 7).

otherwise; and *Summer* is a dummy variable equal to 1 for departures taking place between 21 June and 23 September.

Z_r is a vector accounting for route-characteristics, made up by a set of dummies identifying each of the considered route, where AMS-SXF represents the reference case, and two variables considering the route-level of competition. In detail, *Relative MS* and *Eligible Alternatives* account for direct and inter-modal competition, respectively, and thus help to avoid under-estimated results (Oum et al., 1992). The former variable (*Relative MS*) represents easyJet's market share out of the market share of others low-cost carriers operating on the same route r, computed as the weekly number of flights operated by easyJet on route r divided by the overall number of flights offered by low-cost carriers for the same origin-destination airport pair. *Eligible Alternative* is accounting for all the eligible alternatives to reach all the 21 routes in the sample from the city of Amsterdam. Specifically, an alternative is considered as eligible when the product between its travel time and its average price is whether lower respect to the product of the easyJet alternative or its absolute value is not greater than 20% and at least one between the time or the cost is lower (Morlotti et al., 2017). To download the information about travel cost and travel time of each alternative, this analysis relies on the Rome2rio.com website, a platform providing information about all transport options between origin-destination pairs.[37]

While the X_{irdt} and Z_r vectors of explanatory variables both influence demand and price, Y_{irdt} is characterized by two variables which have an effect on demand and are not determinants of prices, i.e., $PVNAP_{irdt}$ and *Price Drop*. The former, computed as in Equation 5.4, is the price volatility which passengers experience, while *Price Drop* is a dummy variable equal to 1 when $P_{irdt} < P_{ird,t+1}$.[38] This variable is a reminiscent of strategic consumer behaviour as it captures, to some degree, consumer waiting from one day to the next in order to take advantage of lower fares.

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[37] See an example regarding the AMS-SXF route at https://www.rome2rio.com/en/map/Aeroporto-Amsterdam-AMS/Aeroporto-Berlin-Schoenefeld-SXF [accessed on September 2015]

[38] Due to the lack of relevant instruments, the price volatility and price drop variables are not instrumented. This is similar to Gerardi and Shapiro (2009), who do not instrument the HHI in their analysis.

Descriptive statistics of the variables taken into consideration are available in Table 5.3. The average 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). Overall, zero tickets per day were sold in 28.7% of the cases. The average price offered by easyJet's during the period 8 March-23 September, 2015 for the flights departing from the Amsterdam Schiphol airport is €117.22. Interestingly, *Price Drop* indicates that only in the 6.7% of cases passengers experience a drop in prices, thus suggesting that the pricing strategy of easyJet generally sees prices increase i.e., lower fare classes are dynamically closed, as departure day approaches (e.g., Bergantino and Capozza, 2015; Koenigsberg et al., 2008; Stokey, 1979). Price volatility (PVNAP) registers a set of heterogeneous values, ranging from 0 to 0.550, with an average of 0.005. The sample is mainly constituted by observations of flights departing during weekends (50.6% of cases), at peak hours (57.6% of cases) and in spring (58.2% of cases). For what concerns the analysed markets, easyJet is the only low-cost carrier operating on that route in 17 cases over 21, with an average low-cost market share of 92.3% and there is an average of 1.2 alternative transport modes per route, where five routes (out of 21) are served by flights landing from airports close to the ones offered by easyJet.

Table 5.3 – Descriptive statistics of the variables taken into consideration

Variable	Mean	Std. Dev.	Min	Max
Demand	2.396	2.614	0	39
Price	117.219	42.964	29.990	461.990
Price Drop	0.067	0.250	0	1
PVNAP	0.005	0.009	0	0.550
Advance	8.952	6.057	2	45
Booking Weekdays	0.566	0.496	0	1
Departure Weekdays	0.494	0.499	0	1
Peak Hours	0.576	0.494	0	1
Summer	0.418	0.493	0	1
Relative MS	0.923	0.189	0.333	1
Eligible Alternatives	1.230	1.920	0	6

5.4. Results

This section presents the results of the analyses. In Section 5.4.1 regression outcomes are described, while §5.4.2 focuses on the estimates of price elasticity with respect to price volatility.

5.4.1. Regression Analysis

Table 5.4 reports the outcomes of the ordinary least squares (Columns 1 and 2) and the two-stage least squares (Columns 3 and 4) instrumental variable regressions.[39] All the models are consistent and coherent to each other, suggesting that demand is influenced by both flight and route characteristics. Explanatory variables have an interesting impact on demand. Indeed, consumers tend to book more seats as departure day approaches and during booking weekdays. Furthermore, results show that demand is higher for routes where easyJet's market share is lower and there are fewer transport alternatives. According to Brons et al. (2002), the number of alternative modes plays a significant role in determining travellers' price sensitivity and, as Table 5.4 suggests, demand decreases in the presence of a high number of alternative transport options.

As expected, price is negatively associated with demand. This result is confirmed also by the positive value of the *Price Drop* variable, which suggests that generally as the carrier lowers the price, it experiences a higher number of bookings. Such a price drop in generally non-decreasing price pattern used by the carrier, positively stimulates demand or indicate strategic waiting among consumers.

[39] As an alternative to the used instrumental variable, it is used the price lag, computed as the airfare for the same flight a week before, with the same booking days left. Results are provided in Appendix 7.

Table 5.4 – OLS and 2SLS regression estimates on daily demand

Variables	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
Price	-0.0118***	-0.0118***	-0.0103***	-0.0101***
	(0.0002)	(0.0002)	(0.0006)	(0.0007)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Price Drop	0.0888*	0.0762+	0.1066**	0.0983*
	(0.0391)	(0.0402)	(0.0397)	(0.0416)
	[0.0231]	[0.0578]	[0.0073]	[0.0181]
PVNAP		-5.0327***		-5.7370***
		(0.8886)		(1.1596)
		[0.0000]		[0.0000]
Advance	-0.0718***	-0.0717***	-0.0721***	-0.0723***
	(0.0014)	(0.0015)	(0.0017)	(0.0018)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Booking Weekdays	0.8243***	0.8063***	0.8251***	0.8070***
	(0.0194)	(0.0208)	(0.0192)	(0.0205)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Departure Weekdays	0.2437***	0.2690***	0.2648***	0.2931***
	(0.0203)	(0.0218)	(0.0217)	(0.0232)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Peak Hours	0.2572***	0.2603***	0.2381***	0.2383***
	(0.0216)	(0.0231)	(0.0229)	(0.0245)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Summer	0.2994***	0.3526***	0.2805***	0.3301***
	(0.0198)	(0.0212)	(0.0211)	(0.0226)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Relative MS	0.6321***	0.7566***	0.6655***	0.7834***
	(0.1358)	(0.1525)	(0.1310)	(0.1449)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Eligible Alternatives	-0.0601***	-0.0767***	-0.0601***	-0.0762***
	(0.0120)	(0.0134)	(0.0115)	(0.0127)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Constant	3.5474***	3.5341***	3.3590***	3.3318***
	(0.1041)	(0.1138)	(0.1285)	(0.1348)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Observations	58,354	58,354	58,354	58,354
R-squared	0.135	-	0.134	-
F-Statistic	370.92	316.41	303.62	260.66

*Note: ***, **, *, and + indicate significance at the less than 0.1%, 1%, 5%, and 10% levels, respectively. Standard errors in parenthesis and P-values in squared brackets. Hausman test value is 7.48, suggesting there is no endogeneity*[40]

[40] Although the Hausman test suggests there is no endogeneity between prices and demand in the sample, it is aknowledged that purchases are affected by airfares and vice versa. Therefore, the analysis proceeds with the 2SLS estimates, which are very similar to the OLS ones.

Table 5.5 – θ coefficients of the OLS and 2SLS regression estimates on demand

θ	(1) OLS			(2) 2SLS		
	Coefficient	St. Error	P-Value	Coefficient	St. Error	P-Value
0.1	-0.8132**	(0.2509)	0.0012	-1.0162**	(0.3462)	0.0033
0.2	-1.0218***	(0.2846)	0.0003	-1.2528**	(0.3860)	0.0012
0.3	-1.2707***	(0.3247)	0.0001	-1.5347***	(0.4340)	0.0004
0.4	-1.5778***	(0.3730)	0.0000	-1.8822***	(0.4940)	0.0001
0.5	-1.9777***	(0.4338)	0.0000	-2.3334***	(0.5726)	0.0000
0.6	-2.5402***	(0.5167)	0.0000	-2.9648***	(0.6827)	0.0000
0.7	-3.4207***	(0.6453)	0.0000	-3.9469***	(0.8522)	0.0000
0.8	-5.0327***	(0.8886)	0.0000	-5.7370***	(1.1596)	0.0000
0.9	-9.1463***	(1.5683)	0.0000	-10.3147***	(1.9750)	0.0000

*Note: ***, **, *, and + indicate significance at the less than 0.1%, 1%, 5%, and 10% levels, respectively.*

The coefficient of price volatility is significant and negative. This is an important result. Existing literature on price volatility argues that volatile prices expose consumers to higher degree uncertainty, thereby making them less sensitive to changes in prices (e.g., Janiszewski and Lichtenstein 1999). This suggests consumers may end up paying higher prices, but absent is the effect on sales volume. Complementing this literature, the analysis suggests that an increase in price volatility decreases sales. The intuition is as follows. Exposing consumers to price uncertainty decreases their price sensitivity and leads to a wider range of acceptable prices (e.g., Dickson and Sawyer 1990; Janiszewski and Lichtenstein 1999; Kalyanaram and Little, 1994; Murthi et al., 2007; Rao and Sieben, 1992; Winer, 1986). Under these circumstances, sellers can set higher prices in order to increase revenues.[41] However, with higher prices, demand decreases following the basic relationship of price and demand. Indeed, with higher prices a smaller proportion of consumers, who have a sufficiently high willingness to pay, actually purchase the good. The negative relationship occurring between demand and price volatility is consistent across all values of θ.[42]

[41] Another explanation could be that risk averse consumers experiencing fluctuating prices are willing to lock in a price, even if it is higher than the previous days.
[42] See Appendix 8 for results with $PVOLN$ instead of $PVNAP$.

Table 5.4 shows the regression with the value of θ equal to 0.8, which is the standard value used in former literature (e.g., Kalyanaram and Little, 1994; Han et al., 2001), Table 5.5 shows how the PVNAP coefficient varies with the weight given to past price changes with respect to the most recent variation of prices, in the case of OLS and 2SLS regressions (Column 1 and 2, respectively).[43] Interestingly, the more weight is given to past history, the negative is the effect of price volatility on demand.

5.4.2. Estimates of price elasticity

The second step of the analysis aims to estimate passengers' price elasticity according to the different deciles of price volatility. After the two-stage least square regression, it is computed price elasticity of demand at the mean price, which is found to be equal to -0.495. This value suggests that a 10% increase in airfares induces a 5% decrease in air transport demand. Surprisingly, price elasticity of demand is found to be relatively inelastic. The rationale of this result is twofold. First, Amsterdam is recognized to be a business- oriented city (e.g., Morlotti et al., 2017) reflecting the inelasticity associated with high yield business travellers. Second, data is limited for the last 40 seats available, which possibly restricts the bookings observed to those made closer to departure day, where the proportion of high yield business passengers tends to be higher.

As demonstrated in previous studies (e.g., Morlotti et al., 2017; Mumbower et al., 2014), price elasticity is different according to different flight-, booking-, route-, and seasonal-levels and characteristics. By measuring how price sensitivity varies at different levels of price volatility, it is found that price elasticity of demand ranges from -1.883 to -0.439 (see Figure 5.4). Interestingly, it is observed that passengers' price elasticity of demand is inversely related to price volatility. Specifically, in instances with the lowest degree of price volatility, it ranges between -1.2 and -1.9, indicating a very price sensitive demand. As price volatility increases (to the low-medium deciles), price elasticity drops to about -0.7 when

[43] See Appendix 6 for the 2SLS regression with price volatility at different values of θ.

price volatility increases to low-medium level, and with further decrease it maintains a quasi-constant behaviour, hoovering at around -0.5.

By considering the variation in price elasticity with respect to θ, the exponential smoothing factor associated with past price movements, it is observed that generally, as the analysis assumes that consumers associate a larger weight with past movement, the higher is their price sensitivity. This is particularly true for low deciles of price volatility.

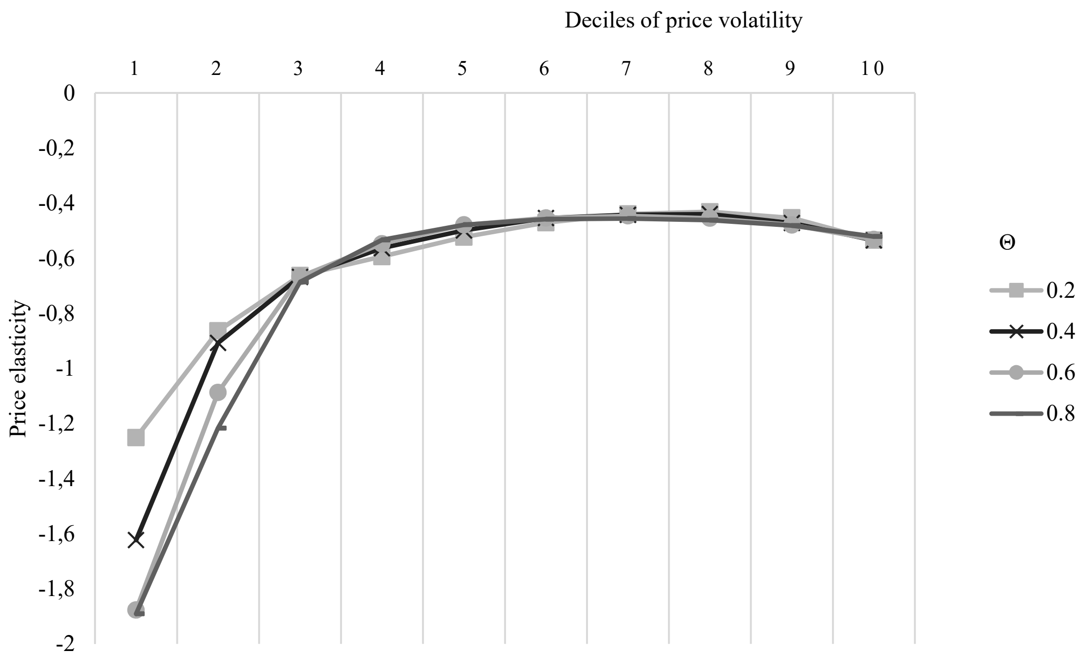

Figure 5.4 - Price elasticity according to the different levels of price volatility

The decreasing of price elasticity of demand as price volatility increases complements previous literature in different markets (e.g., Murthi et al., 2007), where it is shown that an increase in price variability reduces price sensitivities (Janiszewski and Lichtenstein, 1999). The rationale under this relation can be easily explained by taking into consideration that, when prices continuously fluctuate, uncertainty of what should be the "right" price for the product or service that has to be bought arises, therefore leading to a wider range of acceptable prices (e.g., Dickson and Sawyer 1990; Kalyanaram and Little, 1994; Murthi et al., 2007; Rao and Sieben, 1992; Winer, 1986).

5.5. Integration of price volatility into revenue management practices[44]

In this section, it is proposed a simple mechanism to integrate the effects of price volatility into traditional RM practices. The objective to demonstrate the potential impact of price volatility on revenues in light of empirical results. To that end, in Section 5.5, it is considered a simplified illustration using the 3-period EMSR setting, à la Anderson and Wilson (2003). The analysis then proceeds to also account for the potential drawbacks that might exists in the presence of strategic consumers (§ 5.5.2).

5.5.1. EMSR with price volatility

Belobaba (1989) first introduced the expected marginal seat revenue (EMSR) model to guide airlines in setting their optimal booking limits on multiple fare classes. The idea is to maximise revenues by allocating the right number of seats to the different fare classes, considering an overall limited capacity of seats C. Letting f_i denote the average fare of class i, and b_i denote the average number of bookings in class i, airlines seek to maximise their expected revenue with respect of the amount of S_i, i.e., the number of seats allocated to fare class i. Subject to the capacity constraint, the objective function is:

$$R_i(S_i) = \sum_i f_i \cdot b_i(S_i), \text{ for all i.} \tag{5.7}$$

The demand for each fare class i is uncertain. By introducing $p_i(r_i)$ as the probability density function for reservation requests of class i, Belobaba (1989) defines the relative cumulative probability as:

$$P(Si) = P[r_i \leq S_i] = \int_0^{S_i} p_i(r_i) dr_i. \tag{5.8}$$

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44 Existing RM practices ignore the effects induced by price volatility. They take (predicted) demand arrivals as given, without distinguishing between those consumers who arrive for the first time and those who waited before. Further information on modelling consumers behaviour can be found in Anderson and Wilson (2003) and Shen and Su (2009).

Practically, this implies that the probability to receive more than S_i bookings for fare class i is $1 - P$. The expected marginal seat revenue for each class *(*$EMSR_i$) is derived via the first order condition of Equation 3.10 and it can be defined as the average fare level in class i multiplied by the probability of selling S_i or more seats (Belobaba, 1989):

$$EMSR_i = f_i \cdot \overline{P}_i(S_i). \tag{5.9}$$

The (classic) EMSR model assumes that demand for each fare class is distinct and separable, while fare classes are aggregated in order to find the optimal protection levels. To maximise Equation 3.10, the booking limit BL_i, i.e., the maximum number of seats that should be allocated and therefore could be booked in class i, have to be identified. Indeed, to maximise flight revenues, the reservation process should give priority to passengers of class j, which has a higher fare: $f_j > f_i$. Accordingly, the protection level (S_i^j) is the amount of capacity reserved for class j with respect to class i. The optimal protection level satisfies the following condition:

$$EMSR_i(S_i^j) \geq f_i. \tag{5.10}$$

When there are more than two fare classes, the protection level becomes nested, thus including the protection level of class iwith respect to all the other classes with a lower fare. In a framework of $t \in [1; T]$ periods, the nested protection level is:

$$NP_i(t) = \sum_{j \leq i} S_{i+1}^j(t) - \sum_{j<i} S_i^j(t) + b_i^t \tag{5.11}$$

Accordingly, the relationship between booking limits and the nested protection level is dynamically revised as:

$$BL_i(t) = MAX[0, C^{t\text{-}1} - \sum_{j<i} S_i^j(t) - \sum_{j<i} b_j^t], \tag{5.12}$$

where $C^{t\text{-}1}$ is the remained aircraft capacity at the end of period t-1, computed as the initial aircraft capacity C minus the number of booked seats.

This study formulates the numerical illustration based on Anderson and Wilson’s (2003) who provide a 3-period setting illustration of Belobaba’s (1989) EMSR model. Following their example, three fare classes are assumed, namely full class (S_F), saver class (S_S), and supersaver class (S_{SS}), with the objective of setting the nested protection levels for the full and saver fare classes.

Differently from Anderson and Wilson's framework (2003), set prices of different classes are equal to €300, €200, and €100, respectively. In order to integrate price volatility in the model, the three-period scheme is used, splitting the demand distribution from period 3 into two different sub-periods, $3a$ and $3b$ (Table 5.6). Assuming each period lasts one week, period $3b$ is set equal to 1/7 of period 3. Demand for period $3b$ still follows a normal Gaussian distribution (as in Anderson and Wilson, 2003). The new values are computed as:

$$\mu_i^{3b} = 1\text{-}\mu_i^{3a} = 1\text{-}\frac{6}{7}\mu_i^3 \quad (5.13)$$

$$\sigma_i^{3b} = \frac{\mu_i^{3b}\sigma_i^3}{\sqrt{\left({\mu_i^{3a}}^2 + {\mu_i^{3b}}^2\right)}} \quad (5.14)$$

Symmetrically, $\sigma_i^{3a} = \frac{\mu_i^{3a}\sigma_i^3}{\sqrt{\left({\mu_i^{3a}}^2 + {\mu_i^{3b}}^2\right)}}$.

Table 5.6 – Prices, means and standard deviations of arrivals over the three periods, with period 3 split into two sub-periods

Fare Class	**Price (€)**	**Period**							
		$3a$		**$3b$**		**2**		**1**	
		Mean	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**	**Mean**	**St. Dev.**
S_F	300	0.86	0.99	0.14	0.16	7.50	4.69	9.00	3.38
S_S	200	4.29	4.93	0.71	0.82	5.00	5.00	5.00	5.00
S_{SS}	100	7.71	3.33	1.29	0.56	7.50	4.69	1.00	1.00

Apart from the splitting of period 3 into two sub-periods, a key difference from Anderson and Wilson's model, is the introduction of the two parameters needed to take into account price volatility: θ and λ. The former, θ, stands for the smoothing factor (see Equation 5.4), counting for the relevance of past price changes with respect to the last one, while the latter, λ, ranging from 0 to 10, is the factor representing the portion of supersaver consumers which change their price sensitivity in response to price volatility.[45]

The simulation model works as follows. Capacity is fixed at 50 seats and arrivals are distributed as in Table 5.6. Given the arrival of customers in period $3a$, b_F^{3a}, b_S^{3a}, and b_{SS}^{3a} seats are sold to the full save and supersaver classes, respectively. Thus, at the end of this period, a total of $50 - (b_F^{3a}, b_S^{3a}, b_{SS}^{3a})$ seats remain available. To induce price fluctuations, during period $3b$, the supersaver class is closed and it is assumed that the saver class is closed as well with a probability of 50%.[46] As in Belobaba (1989) and Anderson and Wilson (2003), the demand stemming from those closed fare classes is not satisfied, and the price observed by consumers changes from €100 to either €200 or to €300. In period 2 given the unsold seats in period $3b$, price drops randomly to €200 or €100, with a probability of 20% and 80%, respectively and independently from the price set in period $3a$. [47] Given the experienced price volatility, it is assumed that a portion of the supersaver class passengers becomes less price sensitive and they are willing to purchase a saver fare class. This assumption is in line with the findings and the insight that price volatility leads to a wider latitude of acceptable prices and hence a higher willingness to pay (e.g., Murthi et al., 2007). Note that this assumption is restricted to take place only on the supersaver passengers during period 2. Clearly, a broader application of this assumption to other fare classes and to other periods will only amplify the results illustrated below.

To capture the effect of price volatility on consumers, the analysis let λ denote the impact factor of price volatility on supersaver consumers who move to the saver class in period 2, such that the product $\lambda PVNAP_{t-1}$ indicate that proportion of consumers who move up one fare

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[45] λ varies from 0 to 10 as it multiplies price volatility, which, as shown in Table 5.3, has very low values. In details, in the simulation price volatility ranges from 0.01 when $\theta = 0.9$ to 0.1 when $\theta = 0$.

[46] The model does not simply taken into account the arrivals and the capacity left to set price in period $3b$ because of the presence of a feedback loop between the computation of price volatility at period 2 and demand.

[47] Considering that demand of S_{SS} class is not satisfied in period $3a$, the probability of price dropping to €100 is set higher than the probability that price drops to €200. This makes the situation more realistic, especially when strategic consumer behaviour is introduced, as in Section 5.5.2.

class. Specifically, the arrival distribution of the saver class at period 2 (S_S^2) becomes SS_2, while the actual arrivals of the supersaver class ($\widetilde{S_{SS}^2}$) are constituted by the remaining portion, computed as $(1\text{-}\lambda \cdot \mathrm{PVNAP}_{t\text{-}1})S_{SS}^2$.

The model is run 50,000 times for different values of θ and λ, incrementing parameters by 0.1 and 1, respectively. Results suggest an increase in revenues for airlines when introducing price fluctuations (Figure 5.5). When consumers do not respond to price volatility ($\lambda = 0$), on average revenues are equal to €9,207. Gradually, the higher is λ, the higher is the airline's gain, up to a maximum of €9,662 with $\lambda = 10$ and $\theta = 0$, reflecting an increase of almost 5%.

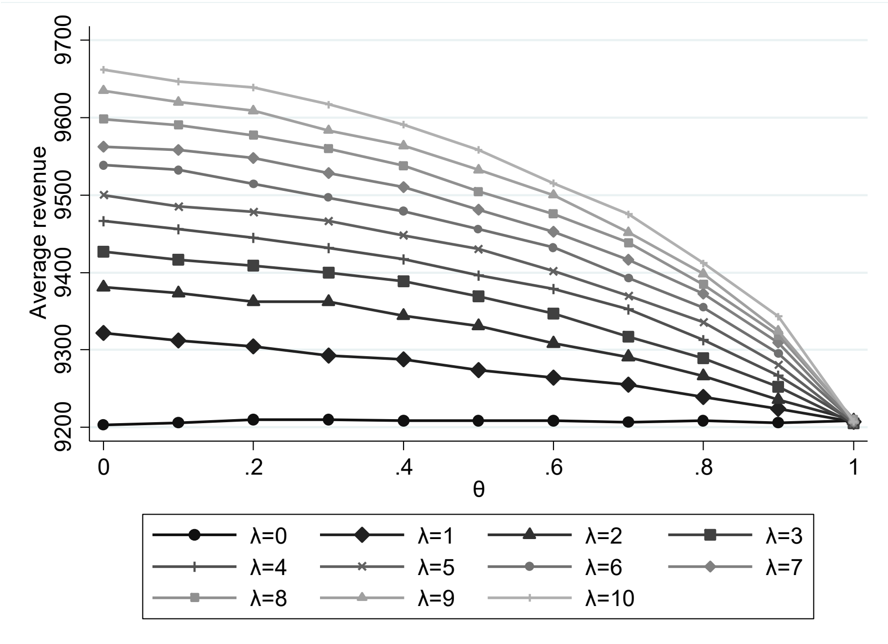

Figure 5.5 – Simulation results for different values of θ *and* λ

While the relationship between revenues and the portion of consumers with a higher willingness to pay linearly increases (λ), θ has an inverse effect on profit, where the maximum amount of revenues is found for $\theta = 0$. That is, when consumers have a better recall of history over response to the most recent price change, then the airline's gain due to price volatility diminishes. Stated differently, the more importance consumers associate with past volatility, the lower is the portion of uncertain consumers who increase their willingness to pay. This insight is not surprising, as it is somewhat driven by the limited horizon considered in this illustration (price volatility is initiated and set to 0 in period $3a$).

5.5.2. EMSR with price volatility and strategic consumers

Consumers become increasingly aware of the benefits of waiting for a price drop and accordingly many behave strategically in timing their purchase (e.g., Cachon and Swinney, 2009, Aflaki et al., 2018). The availability of online fare prediction tools supports such behaviour, which could result with a significant revenue loss (Mantin and Rubin, 2016). Such a behaviour could counteract the benefits generated by price volatility. Namely, whereas some consumers will get confused and ultimately will be willing to pay a higher price, those who behave strategically will time their behaviour to take advantage of potentially lower prices in the future. To this extent, the numerical illustration is extended and a proportion ψ of the saver class consumers is assumed to behave strategically. Such a behaviour could be supported either by fare prediction tools or simply by daily monitoring of fares. Such online tools often provide a simplified suggestion on whether to buy now or wait (one period) for a potentially better fare.

To integrate strategic consumer behaviour, these consumers are assumed to decide to postpone their purchases only if the probability of a cheaper fare class opening in the next period exceeds some certain threshold, τ (see Mantin and Rubin, 2016, for an illustration of the *Farecast* application that provided a forecast treating a period of seven days as a single period and deriving a threshold-based recommendation).[48] Accordingly, similar to Anderson and Wilson (2003), starting from the end of period $3b$, where $3b = t - 1$, it is computed the probability that the supersaver class opens at period t, $\mathrm{P}[\mathrm{C}^{t\text{-}1} > \mathrm{NP}_{\mathrm{SS}}^{t}]$, i.e., this is the

[48] Technically, it is possible to assume that consumers are *super strategic*, in the sense that they may consider waiting more than one period. However, this makes the numerical model intractable and, qualitatively, it is expected *super strategic* consumer behaviour to yield insights consistent with the insights derived in this subsection.

probability that the remaining capacity at the end of period $t\text{-}1$ exceeds the nested protection level associated with the supersaver class (which the number of seats reserved for saver and full classes) at period t. This implies that strategic consumers who arrive at period $t\text{-}1$ can choose whether to buy or wait. If their fare class is close, they will wait for one period if $P[C^{t\text{-}1} > NP_{SS}^{t}] \geq \tau$. Otherwise, they try to book seats at the original saver fare at period $t\text{-}1$.

The combined effects of price volatility and strategic consumers is articulated through the arrival of the different consumers over time and their associations with the different fare classes. On the one hand, price volatility induces non-strategic supersaver consumers to accept saver fares but, on the other hand, it induces strategic saver consumers to possibly wait in expectation of purchasing at the lower supersaver fare. Specifically, in the model, when $P\left[C^{3b} > NP_{SS}^{2}\right] \geq \tau$, the strategic saver consumers who arrive in period $3b$, $\psi \cdot S_{S}^{3b}$, do not book any seat and waits for a supersaver fare in period 2, and the arrival distribution of the supersaver class in period 2, adjusted for the effects of price volatility, $\widetilde{S_{SS}^{2}}$, becomes $(1\text{-}\lambda \cdot PVNAP_{t\text{-}1})S_{SS}^{2} + \psi \cdot S_{S}^{3b}$. Since strategic consumers are generally more engaged and active about the timing of the purchase, the analysis assumes that they are served first in period 2. Some of the new saver consumers also behave strategically, so that they may delay their purchase decision to period 1. Thus, when $P\left[C^{3b} > NP_{SS}^{2}\right] > \tau$ saver class consumers arrival at period 2 ($\widetilde{S_{S}^{2}}$) becomes:

$$\widetilde{S_{S}^{2}} = \begin{cases} (1\text{-}\psi)S_{S}^{2} & \text{if } b_{SS}^{2} \geq \psi \cdot S_{S}^{3b}, P[C^{2} > NP_{SS}^{1}] > \tau \\ (1\text{-}\psi)S_{S}^{2} + b_{SS}^{2}\text{-}\psi \cdot S_{S}^{3b} & \text{if } b_{SS}^{2} < \psi \cdot S_{S}^{3b}, P[C^{2} > NP_{SS}^{1}] > \tau \\ S_{S}^{2} & \text{if } b_{SS}^{2} \geq \psi \cdot S_{S}^{3b}, P[C^{2} > NP_{SS}^{1}] \leq \tau \\ S_{S}^{2} + b_{SS}^{2}\text{-}\psi \cdot S_{S}^{3b} & \text{otherwise} \end{cases} \tag{5.15}$$

where b_{SS}^{2} is the bookings for the supersaver available seats in period 2. In the other cases, the distribution of $\widetilde{S_{S}^{2}}$ is equal to $(1\text{-}\psi)S_{S}^{2}$ if $P[C^{2} > NP_{SS}^{1}] > \tau$, otherwise the arrivals remain unchanged ($\widetilde{S_{S}^{2}} = S_{S}^{2}$).

Finally, in period 1, no strategic consumers are assumed to wait. Rather, if $P[C^{2} > NP_{SS}^{1}] > \tau$, the arrival of supersaver passengers ($\widetilde{S_{SS}^{1}}$) become $S_{SS}^{1} + \psi \cdot S_{S}^{2}$, while S_{S}^{1} remains unchanged unless $b_{SS}^{1} \leq \psi \cdot S_{S}^{2}$, when it becomes $S_{S}^{1} + b_{SS}^{1}\text{-}\psi \cdot S_{S}^{2}$.

The model is run 50,000 times for different values of λ, θ, τ and ψ in order to account for both price volatility and strategic consumers, for a total of 14,641 combinations. First it is illustrated the effect of strategic consumers while abstracting away from the effects of price volatility as inducing higher willingness to pay. Figure 5.6 shows the average revenues varying according to the minimum probability value driving saver consumers to wait (τ) and the proportion of strategic consumers (ψ). Two intuitive insights are visible: the average revenues decrease in the fraction of strategic consumers (decreasing by up to 2.5% from €9,207 when there are no strategic consumers to €8,976 when all saver consumers in period 2 behave strategically with $\tau = 0$) and that revenues increase in the threshold value, τ. Namely, as consumers are more cautious in their waiting decision, the loss due to the presence of strategic consumers is capped.

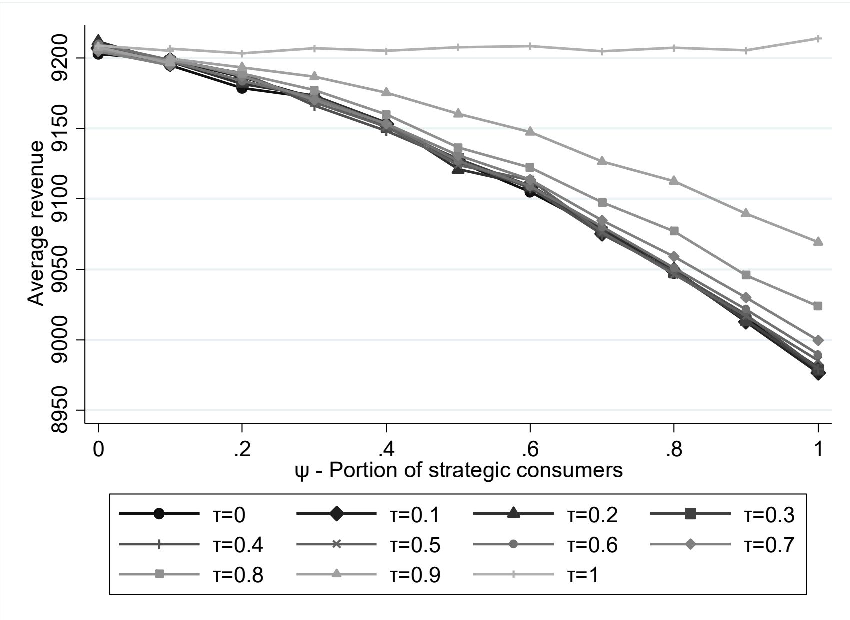

Figure 5.6 - Simulation results for different values of τ*, the waiting threshold, and* ψ*, the proportion of strategic consumers, when prices fluctuations are not introduced*

Next, the analysis turns the attention to the combined effect of price volatility and strategic consumers (Figure 5.7). In Figure 5.7a, simulation results are provided for characteristic instances where $\tau = 0.8$, a rather high threshold for waiting, and $\lambda = 2$, a rather limited impact of volatility on willingness to pay. Coherently with former outcomes, revenues decrease in the proportion of strategic consumer increases, ψ, and in the smoothing constant, θ. By comparing these results with Figure 6, when $\lambda = 2$ revenues range from €9,208 ($\theta = 1$) to €9,381 ($\theta = 0$), similar to what is depicted in Figure 5.7a when $\psi = 0$ (from €9,205 to €9,376). Although accounting for price volatility has a positive effect on revenues, due to the decreased consumers' price sensitivity, strategic consumers have a negative value on revenues, reaching a minimum value of €9,024 when $\theta = 1$ and $\psi = 1$. This value is 2.0% lower than the minimum value without strategic consumers (€9,207) but still 0.5% higher with respect to the case with strategic consumers and not accounting for price volatility (€8,976). Consistently, Figure 5.7b illustrates how revenues vary for different values of ψ and λ, when the probability threshold (τ) is equal to the 50% and $\theta = 0.8$. The dashed red line represents the average revenue value when no strategic consumers and no price volatility are included in the model (around €9,207). This figure shows the trade-off due between the presence of strategic consumer and the portion of consumer whose willingness to pay increase due to price volatility. In details, there is only one case ($\psi = 0$) in which revenues are always higher than €9,207, ranging from €9,207 to €9,414, and two cases ($\lambda = 9$ and $\lambda = 10$) in which revenues are below €9,207, ranging from a minimum of €8,980 (€9,015) to a maximum of €9,145 (€9,187) when $\lambda = 10$ ($\lambda = 9$). In all the other simulations, price volatility and the portion of strategic consumers impact differently on revenues. Asψdecreases, there is the need of a lower portion of consumers with a higher willingness to pay, conditioned to price volatility, to have revenues above €9,207.

In both figures, there is a clear evidence on how the presence of strategic consumers may have an impact on airlines' revenues, even if price volatility generally decreases consumers' price sensitivity. Practically, the extent to which it is convenient to induce price volatility in revenue management practices strongly depends on the percentage of strategic consumers in the market. Recently, several scholars attempt to assess the proportion of strategic consumers and to map their purchasing behaviour. However, there is still no clear agreement in the literature neither on their amount, found to vary from 5% to more than 70%, nor on their effect on revenues (e.g., Li et al., 2014; Osadchiy and Bendoly, 2015).

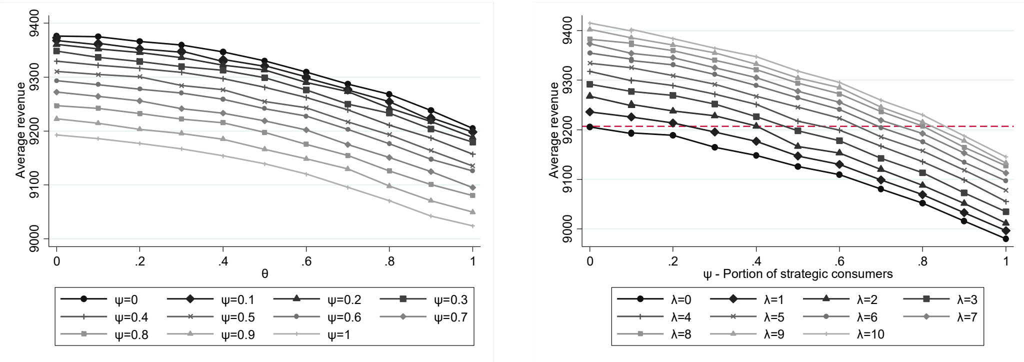

Figure 5.7 – Simulation results for different values of θ *and* ψ *with* $\tau = 0.8$ *and* $\lambda = 2$ *(Figure 5.7a) and for different values of* ψ *and* λ *with* $\tau = 0.5$ *and* $\theta = 0.8$ *(Figure 5.7b)*

5.6. Conclusion

This study contributes to the ever-growing literature on revenue management and consumer behaviour by highlighting a key outcome the often emerges from practicing revenue management: volatile prices. The implications of price volatility may differ from those derived previously for consumer packaged goods, as, for example, revenue-managed good exhibit somewhat predictable price trajectories and consumers may expect those price movements.

Before carrying out the empirical analysis, a revised measure of price volatility, PVNAP, is proposed, which takes into account both the differences across the studied routes and the predictability of airfares. Using air tickets as a sample industry, the 2SLS IV estimations reveal that higher prices lead to a decrease in demand, as expected, but that the greater the variation in prices (as captured by the measure PVNAP), the lower is the number of tickets purchased. This outcome sheds light on the fact that prices fluctuations tend to negatively influence consumers' purchasing propensity.

By computing price elasticity of demand with respect to different levels of price volatility, evidence of a strong negative correlation is found: as price volatility increases, consumers exhibit a lower price sensitivity. This result complements the literature, which states that as when consumers are subject to a higher price uncertainty, their range of acceptable prices is distorted as well as their value of the reference price (Dickson and Sawyer, 1990; Kalyanaram and Little, 1994; Rao and Sieben, 1992; Winer, 1986;). The analysis further generalizes the insights as follows. Price volatility induces demand to be less elastic, which could lead firms to increase prices, so consumers may end up paying more. At the same time, higher prices possibly reduce the pool of consumers who are willing (or able) to purchase, thereby potentially reducing the overall demand. Hence, firms need to weigh carefully the benefit of inducing price volatility with the lost demand to ensure they properly craft their inter-temporal prices.

Existing RM practices ignore the effects induced by price volatility. Literature takes (predicted) demand arrivals as given, and the aggregate effects on consumers are not taken into account. Outcomes on price elasticity clearly indicate that consumers respond to price fluctuations, indicating the presence of impact that is, at the moment, ignored by RM systems. Accordingly, this chapter illustrates how the introduction of the effects of price volatility may play out in a revenue management environment. To that end, an EMSR model (Belobaba, 1989) is developed following the example of Anderson and Wilson (2003) as a benchmark, to demonstrate how inducing price volatility can generate an increase in revenues of up to 2.5% in the setting. Importantly, the analysis further accounts for the presence of strategic consumers, which can yield a detrimental impact revealing a trade-off as with more such consumers the benefit of inducing volatile prices diminishes and can even be negative.

This study opens avenues for ample future research. First, the empirical analysis could be enlarged both in terms of routes, departing from airports other than Amsterdam, and in terms of airlines which may apply a less (or more) incisive dynamic pricing. Second, by having data on broader demand – i.e., not just considering the last 40 seats available – it is possible to estimate how price volatility influences elasticity also of typically more price sensitive passengers, who are known to book in advance. It is expected that the impact of price volatility on price elasticity is higher when bookings occur several days before departure and airline could greatly rely on price changes to influence demand. Further, the simulation model assumes a monopolistic market where the firm does not lose consumers when raising prices and only three periods. To that end, from the one hand, it would be constructive to consider competition, as inducing price volatility in competitive environments could result with consumers defecting to competitors, and hence a decrease in revenues (Belobaba and Wilson, 1997). To the other hand, including more periods it would be interesting to map the possibility for consumers to wait for more than one periods and having different thresholds (τ) at different points in time. Lastly, encapsulating these insights in an analytical model could ultimately provide firms with concrete guidance on when and how to induce price volatility.

Chapter 6 – General Conclusion

With the aim to analyze the relationship between demand and prices in the air transport industry, this thesis addresses new interesting research questions in the field of revenue management studies. By taking a consumer perspective, it is explored whether there are additional strategies applied by airlines to price discriminate in the market. Further, passengers' price sensitivity and its variations are studied, according to both external characteristics (e.g., seasonal and market dimension) and the intensity of dynamic pricing approach.

In details, this work first extends the literature on carriers' pricing strategies by investigating the presence of a new form of price discrimination. The multitude of studies on airlines pricing strategies finds a relation between airfares and market, time, and flight characteristics, overlooking the extent to which there exist a relation between the number of seats purchased and the unitary applied price. By searching for price differentials based on the number of seats booked by a single consumer, evidence shows the presence of a two-part tariff system in the offered fares, which inevitably generates quantity discounts. However, the relation between quantity and unitary price is not linear. Rather, the lowest average unit price is associated with a single consumer reserving 5 seats. On average, the per-seat discount for a single consumer reserving 5 seats is €9.48, which is 14% of the single-seat fare. This form of price discrimination does not substitute the acknowledged dynamic pricing approaches already examined by scholars. Unitary prices are still found to vary according to different factors, such as the number of available seats, the days left to departure, and other characteristics. Also quantity discounts present variations accordingly: quantity discounts are greater for flights with a larger fraction of available seats at the time of booking, when seats are booked longer in advance, and the destination's gross domestic product per capita is greater. Conversely, quantity discounts are lower for longer routes, larger destination airports, and routes for which the airline's market share is higher.

Second, this thesis contributes to the literature by estimating price elasticity of European passengers. As the average price elasticity does not properly capture passengers' heterogeneity, price elasticity of demand is computed according to seasonal, market, booking and flight characteristics. Results suggest that 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. Generally, 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. Interestingly, all results can be commented in light of the typical airline market segmentation, disentangling between high yield/business and leisure consumers. Alternatively, this study helps in identifying the presence of strategic passengers, i.e., passengers who monitor prices and time their purchases in order to pay as less as possible (e.g., Cachon and Swinney, 2009; Li et al., 2014), who are recognised to be sensitive to prices and their variations.

In this framework, this thesis eventually explores whether price fluctuations, which are the direct consequence of revenue management implementation, may influence consumers' price sensitivity. After identifying a proper measure of price volatility, which already captures the predictability of prices studied in previous literature, it is estimated the effect of price volatility on demand and on price elasticity of demand. Empirical analyses reveal that with higher degrees of price volatility (i.e., above and beyond the predicted price trajectory), demand decreases. Previous studies on price volatility find that price fluctuations lead to a higher degree of uncertainty, which makes consumers less sensitive to price changes (e.g., Janiszewski and Lichtenstein, 1999). The combination of an increased uncertainty and a consequent lower price sensitivity induces consumers to pay higher prices. Indeed, price elasticity decreases in price volatility, ranging from -1.883 to -0.439 at low and high degrees of price volatility, respectively. Generally, results suggest that the effect of price volatility on airlines' profitability is not clear. Indeed, while exposing consumers to price uncertainty decreases their price sensitivity and leads to a higher paid price, the overall demand is reduced (given the higher prices). This insight leads to incorporate the impact of price volatility on consumers behaviour into the classical revenue management model (Expected Marginal Seat Revenue), demonstrating its potential implementation benefit in increasing revenues. However, some consumers may take advantage from the increasing uncertainty generated by price volatility. The extent to which inducing price volatility is beneficial for airlines strictly depends on the percentage of strategic consumers, who wait price drops to purchase. In this sense, uncertainty, which usually has a negative connotation, works as a stimulus for strategic consumers to monitor prices and thus properly time their purchases.

Overall, this thesis gives new insights on the dynamics between prices and demand in the air transport industry, especially in light of the presence of strategic consumers. Identifying airlines price discrimination strategies gives more information to passengers who would like to act strategically, thus potentially harming airlines' profitability. Consumers' knowledge about price discrimination according to time and flight- and booking- characteristics are already known to play a role in influencing airlines' revenues (e.g., Li et al., 2014). Likely, passengers' awareness of the presence of a two-part tariff system with quantity discounts could lead to different booking patterns, whose effects on revenues should be investigated. Furthermore, information on consumers price elasticity may help airlines in identifying those markets, periods and flight or booking characteristics for which it is more probable to deal with strategic consumers. Indeed, price elasticity results may support airlines pricing decision, by giving information needed to forecast the impact of a potential change in their flight offerings varying according to seasonality, markets, and also departure and reservation days. At the same time, recognising more elastic markets it is possible for passengers to detect the likelihood that airlines plan price drops, as in presence of price elastic consumers it could be profitable to offer temporary discounts to stimulate demand and recover the possible unexpected booked quantity. Even if both airlines and consumers may act strategically by leveraging on information on price elasticity, the effect that a price change per se has on revenues – therefore on consumers' purchasing behaviour – cannot be neglected. Price fluctuations generates uncertainty (e.g., Murthi et al., 2007), thus decreasing consumers price sensitivity and, at the same time, enlarging the ranges of acceptable prices. Although this generally leads to a higher price paid, the overall effect on demand is negative. This causes a trade-off which has to be properly evaluated by airlines. Whilst introducing price fluctuations may lead to an increase in revenues thanks to the increasing consumers' willingness to pay (which lead airlines to increase prices), there is the possibility that the number of remaining available seats increases, due to the overall decrease in demand. This causes a discrepancy between expected demand and realized one, which leads airlines to make downward price adjustments to stimulate demand. Strategic consumers wait these price reductions to make their purchases. Before introducing price fluctuations, airlines should therefore pay attention on the presence and evaluate the portion of strategic consumers present in the market, in order to effectively maximise their revenues.

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Appendixes

Appendix 1: Quantity discounts by destination

Quantity discounts vary according to route characteristics, such as the level of competition, the GDP per capita, and the market size.

Table A.1 – Discount statistics by destination

Destination	Discount				Mean of	Mean of
	Mean	St. Dev	Min	Max	$P_{it}(1)$	$P_{it}(5)$
BFS	0.1226	0.0641	-0.1627	0.3530	86.8167	77.0719
BOD	0.1818	0.0776	-0.0360	0.4001	64.3046	53.7475
BRS	0.0855	0.0590	-0.1912	0.2667	115.5741	105.5436
BSL	0.1665	0.1079	-0.1035	0.4446	78.2026	67.5944
EDI	0.1225	0.0584	-0.1391	0.3001	86.7145	75.5760
FCO	0.0828	0.0520	-0.5165	0.2239	102.9032	94.1911
GLA	0.1114	0.0566	-0.0783	0.3001	88.8322	78.9801
GVA	0.1573	0.0949	-0.1346	0.4287	78.9593	68.1474
HAM	0.3182	0.1142	-0.1303	0.4802	41.9261	30.4341
LGW	0.1554	0.0878	-0.1423	0.3751	78.3013	67.9955
LIS	0.0825	0.0474	-0.0727	0.1846	112.2449	100.2501
LPL	0.1188	0.0829	-0.2518	0.4139	93.4882	82.9816
LTN	0.1711	0.0957	-0.1188	0.3751	73.2876	62.7380
MAN	0.1166	0.0755	-0.1108	0.3637	97.8532	86.3311
MXP	0.1183	0.0724	-0.1869	0.4001	95.2104	84.1279
NCL	0.1107	0.0679	-0.0800	0.3430	92.6027	83.1230
PRG	0.0917	0.0536	-0.1217	0.2353	105.6869	94.1234
SEN	0.1854	0.0975	-0.2079	0.4139	66.5579	55.5861
STN	0.1605	0.0884	-0.1778	0.3530	75.1668	64.8154
SXF	0.1489	0.0737	-0.1556	0.3872	74.8503	64.4793

Table A.1 provides descriptive statistics of discounts by route. The highest value is registered for Hamburg, whose average discount is equal to 32%, while the lowest value (8%) is registered for the Amsterdam-Rome Fiumicino route. The extent to which multiple reservations are made depends on the nature of the destination, which may attract group of people or families. To investigate whether there exists a difference in the average discount offered for such kinds of routes, this study relies on the easyJet classification of destinations, according to which it is appropriate for family holidays ("Family holidays") or it is close to the seaside ("Beach").[49] Table A.2 shows that there is a significant difference among family (beach) and non-family (non-beach) destinations, where the average discount is higher for family (beach) destinations. This suggests that easyJet tend to offer quantity discounts especially to destinations close to the seaside and that are preferred by families.

Table A.2 – T-test on discount by "Family Holidays" and "Beach" destinations

Group	Discount						Ho: diff != 0	
	Obs	Mean	Std. Err	St. Dev	[95% Conf. Interval]		t-statistic	Pr(|T| > |t|)
0- No Family Holidays	33,682	0.1373	0.0005	0.0937	0.1363	0.1383	-18.7027	0.0000
1-Family Holidays	41,633	0.1499	0.0004	0.0905	0.1490	0.1507		
0- No Beach	72,928	0.1440	0.0003	0.0924	0.1433	0.1447	-3.5523	0.0004
1-Beach	2,387	0.1508	0.0017	0.8342	0.1475	0.1542		

[49] Destination classifications are available at http://www.easyjet.com/en/routemap.

Appendix 2: 3SLS Regression results

Table A.3 – 3SLS regression estimates on demand as in Chapter 4

	3SLS		
	Coefficient	**Robust St. Error**	**P-value**
Price	-0.0153**	(0.0054)	0.0043
Eligible Alternatives	-0.0562***	(0.0121)	0.0000
LC Dominance	0.7221***	(0.1609)	0.0000
Departure Hours (Evening is the ref. case)			
Morning	-0.0651	(0.0761)	0.3922
Lunchtime	-0.2509***	(0.0633)	0.0001
Afternoon	-0.0725*	(0.0334)	0.0300
Departure Days (Saturday is the ref. case)			
Sunday	-0.0644***	(0.0018)	0.0000
Monday	0.4068*	(0.1677)	0.0153
Tuesday	0.5624***	(0.0416)	0.0000
Wednesday	0.8250***	(0.0619)	0.0000
Thursday	0.8099***	(0.0666)	0.0000
Friday	0.9055***	(0.0379)	0.0000
Reservation Days (Saturday is the ref. case)			
Sunday	0.1410***	(0.0348)	0.0001
Monday	1.5353***	(0.0350)	0.0000
Tuesday	1.4917***	(0.0355)	0.0000
Wednesday	1.4919***	(0.0363)	0.0000
Thursday	1.3954***	(0.0357)	0.0000
Friday	1.2411***	(0.0341)	0.0000
Month (September is the ref. case)			
March	-0.5390***	(0.1233)	0.0000
April	-0.3860***	(0.0377)	0.0000
May	-0.4363***	(0.0502)	0.0000
June	-0.2225**	(0.0682)	0.0011
July	0.1733*	(0.0781)	0.0264
August	-0.3322***	(0.0390)	0.0000
Advance	-0.0644***	(0.0018)	0.0000
Constant	3.2730***	(0.7571)	0.0000
Observations		66,716	
X^2*-statistic*		561.412	

Note: ***, **, *, and + indicate significance at the less than 0.1%, 1%, 5%, and 10% levels, respectively.

Table A.4 – 3SLS regression estimates on demand as in Chapter 5

Variables	(1) OLS	(2) OLS
Price	-0.0103***	-0.0101***
	(0.0006)	(0.0007)
	[0.0000]	[0.0000]
Price Drop	0.0863*	0.0731+
	(0.0397)	(0.0416)
	[0.0296]	[0.0784]
PVNAP		-4.8400***
		(1.1589)
		[0.0000]
Advance	-0.0720***	-0.0721***
	(0.0017)	(0.0018)
	[0.0000]	[0.0000]
Booking	0.8253***	0.8074***
Weekdays	(0.0192)	(0.0205)
	[0.0000]	[0.0000]
Departure	0.2646***	0.2929***
Weekdays	(0.0217)	(0.0232)
	[0.0000]	[0.0000]
Peak Hours	0.2381***	0.2379***
	(0.0229)	(0.0245)
	[0.0000]	[0.0000]
Summer	0.2804***	0.3299***
	(0.0211)	(0.0226)
	[0.0000]	[0.0000]
Relative MS	0.6663***	0.7848***
	(0.1309)	(0.1448)
	[0.0000]	[0.0000]
Eligible	-0.0602***	-0.0762***
Alternatives	(0.0115)	(0.0127)
	[0.0000]	[0.0000]
Constant	3.3590***	3.3249***
	(0.1285)	(0.1347)
	[0.0000]	[0.0000]
Observations	58,354	58,354
χ^2-*statistic*	303.62	7,282.74

To estimate the coefficients of demand and price simultaneously, the analysis from Table 4.1 and Table 5.4 is repeated by using a three-stage least square regression model. In both cases, consistent with the OLS and 2SLS outcomes, 3SLS regression results corroborate the negative correlation between demand, prices, and price volatility (Table A.3 , Table A.4, and Table A.5).

Table A.5 – θ coefficients of the 3SLS regression estimates on demand

θ	3SLS		
	Coefficient	St. Error	P-Value
0.1	-0.7604*	(0.3460)	0.0280
0.2	-0.9614*	(0.3858)	0.0127
0.3	-1.2012**	(0.4337)	0.0056
0.4	-1.4971**	(0.4936)	0.0024
0.5	-1.8827**	(0.5723)	0.0010
0.6	-2.4256***	(0.6823)	0.0004
0.7	-3.2771***	(0.8517)	0.0001
0.8	-4.8400***	(1.1589)	0.0000
0.9	-8.8378***	(1.9737)	0.0000

*Note: ***, **, *, and + indicate significance at the less than 0.1%, 1%, 5%, and 10% levels, respectively.*

Appendix 3: Correlation matrix and regression relationships

Table A.6 and Table A.7 present the correlation matrix of the variables included in the model of Chapter 4 and Chapter 5, respectively. Figure A.1 shows the relationship between real and fitted values of demand with respect to price and days to departure.

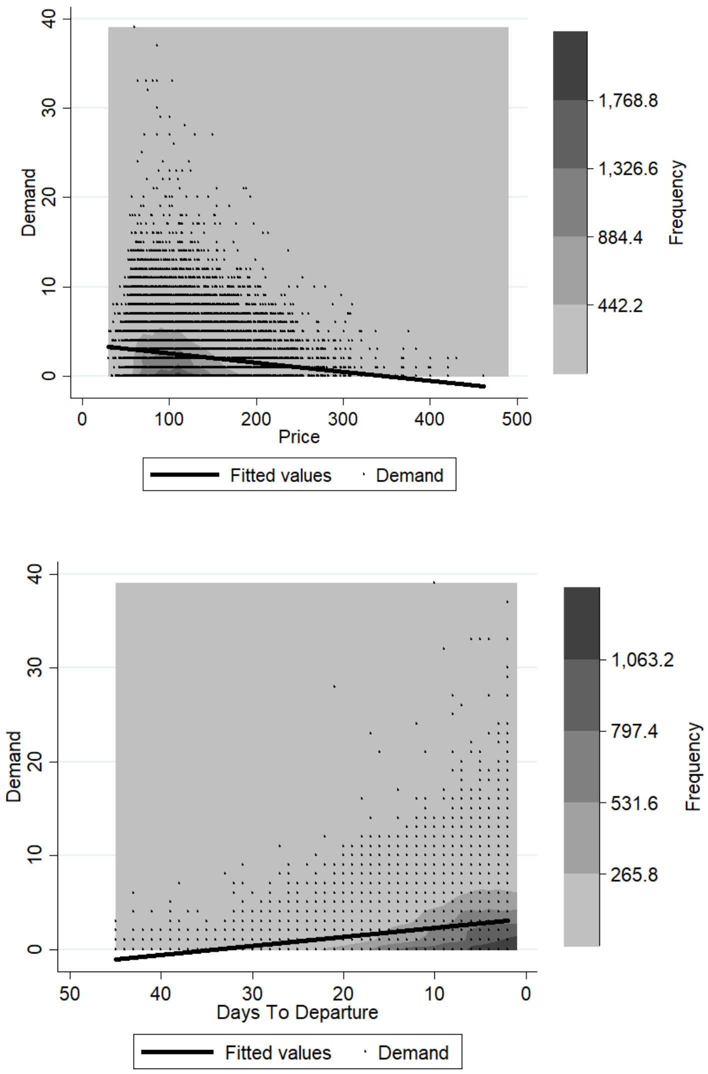

Figure A.1 – Real and fitted values of demand with respect to price and days to departure

Table A.6 – Correlation matrix of variables included in the model in Chapter 4

	Dem.	*Price*	*Eligible Alt.*	*LC Dom.*	*Mor.*	*Lunch.*	*Aftern.*	*Adv.*
Demand	1							
Price	-0.1687	1						
Eligible Alternatives	0.1026	-0.0460	1					
LC Dominance	0.0108	-0.0825	0.2350	1				
Morning	0.0454	-0.1503	-0.0416	-0.0424	1			
Lunchtime	-0.0736	-0.0013	-0.0262	0.1498	-0.2680	1		
Afternoon	-0.0160	0.0247	0.0334	-0.0228	-0.2575	-0.2038	1	
Advance	-0.2232	0.0455	-0.1369	0.0057	-0.0321	0.1271	-0.0211	1
D.Sunday	-0.0938	0.2857	0.0845	-0.0152	-0.1473	-0.0934	0.1554	0.0903
D.Monday	-0.0002	-0.0257	-0.0131	0.0383	0.0267	0.0147	-0.0871	-0.0140
D.Tuesday	0.0624	-0.1065	-0.0146	-0.0058	0.0315	-0.0331	-0.0446	-0.0473
D.Wednesday	0.0550	-0.0822	-0.0419	-0.0562	-0.0414	0.0385	-0.0416	-0.0566
D.Thursday	0.0694	-0.0570	-0.0205	0.0204	0.0346	-0.0062	-0.0373	-0.0750
D.Friday	0.0217	-0.0300	-0.0234	-0.0063	-0.0136	0.0245	-0.0187	-0.0439
R.Sunday	-0.1325	-0.0152	0.0009	-0.0027	-0.0008	-0.0003	-0.0013	0.0061
R.Monday	0.0830	-0.0064	-0.0021	-0.0029	0.0010	0.0037	-0.0009	-0.0099
R.Tuesday	0.0718	0.0074	0.0007	0.0007	0.0069	0.0044	0.0011	-0.0127
R.Wednesday	0.0657	0.0042	-0.0029	-0.0053	0.0013	0.0031	0.0020	-0.0033
R.Thursday	0.0487	0.0027	-0.0035	0.0006	-0.0013	-0.0021	0.0041	0.0077
R.Friday	0.0281	0.0155	0.0021	0.0046	-0.0075	-0.0064	0.0014	0.0012
March	-0.0160	-0.1112	-0.0314	-0.0100	-0.0769	0.0020	0.0568	0.0019
April	-0.0209	0.0011	0.0101	0.0191	0.0311	-0.0233	-0.0021	0.0508
May	-0.0326	-0.0304	-0.0036	0.0143	0.0413	-0.0088	-0.0043	0.0042
June	0.0256	-0.0520	-0.0012	0.0073	0.0031	-0.0052	-0.0261	-0.0373
July	0.0228	0.1522	-0.0060	-0.0298	-0.0168	0.0213	0.0076	0.0393
August	-0.0150	0.0194	0.0243	-0.0038	0.0010	0.0150	-0.0220	-0.0242

	D.Sun.	*D.Mon.*	*D.Tue.*	*D.Wed.*	*D.Thu.*	*D.Fri.*	*R.Sun.*	*R.Mon.*
D.Sunday	1							
D.Monday	-0.2307	1						
D.Tuesday	-0.1733	-0.1512	1					
D.Wednesday	-0.1775	-0.1549	-0.1163	1				
D.Thursday	-0.1874	-0.1635	-0.1228	-0.1258	1			
D.Friday	-0.2291	-0.1999	-0.1501	-0.1538	-0.1624	1		
R.Sunday	-0.0238	-0.0461	0.0443	0.0314	0.0191	0.0001	1	
R.Monday	-0.0112	-0.0324	-0.0472	0.0453	0.0298	0.0173	-0.1669	1
R.Tuesday	-0.0047	-0.0165	-0.0301	-0.0498	0.0457	0.0378	-0.1648	-0.1670
R.Wednesday	0.0135	-0.0029	-0.0128	-0.0308	-0.0503	0.0500	-0.1639	-0.1661
R.Thursday	0.0339	0.0188	0.0021	-0.0120	-0.0306	-0.0497	-0.1639	-0.1661
R.Friday	0.0380	0.0297	0.0137	-0.0006	-0.0168	-0.0362	-0.1666	-0.1688
March	0.0981	0.0166	-0.0254	-0.0497	-0.0072	-0.0175	0.0081	-0.0001
April	-0.0357	-0.0283	0.0249	0.0381	0.0515	-0.0153	-0.0141	-0.0160
May	-0.0010	-0.0234	-0.0111	-0.0101	-0.0209	0.0193	0.0091	0.0047
June	-0.0014	0.0246	0.0092	-0.0219	-0.0095	-0.0075	0.0074	-0.0059
July	-0.0195	-0.0098	-0.0311	0.0366	0.0028	0.0284	-0.0076	-0.0084
August	-0.0202	0.0268	-0.0057	0.0134	-0.0087	-0.0099	0.0021	-0.0057

	R.Tue.	*R.Wed.*	*R.Thu.*	*R.Fri.*	*March*	*April*	*May*	*June*
R.Tuesday	1							
R.Wednesday	-0.1639	1						
R.Thursday	-0.1640	-0.1631	1					
R.Friday	-0.1666	-0.1657	-0.1658	1				
March	-0.0155	-0.0017	-0.0022	-0.0015	1			
April	0.0129	-0.0140	-0.0121	0.0371	-0.1762	1		
May	-0.0388	-0.0276	0.0234	0.0205	-0.1697	-0.2133	1	
June	-0.0223	-0.0192	0.0103	0.0154	-0.1641	-0.2063	-0.1987	1
July	0.0372	0.0216	-0.0112	-0.0162	-0.1456	-0.1830	-0.1763	-0.1705
August	0.0156	0.0315	-0.0187	-0.0306	-0.1512	-0.1900	-0.1830	-0.1770
	July	*August*						
July	1							
August	-0.1570	1						

Note: D. stands for departure day, while R. for reservation day.

Table A.7 – Correlation matrix of the variables taken into consideration in Chapter 5

	Demand	*Price*	*Price Drop*	*PVNAP*	*Advance*	*Booking Weekdays*	*Dep. Weekdays*	*Peak Hours*	*Summer*	*Relative MS*	*Eligible Altern.*
Demand	1										
Price	-0.1700	1									
Price Drop	-0.0056	-0.0546	1								
PVNAP	-0.0152	0.0845	0.0656	1							
Advance	-0.2239	0.0599	0.0981	-0.0649	1						
Booking Weekdays	0.0790	-0.1388	-0.0304	0.0106	-0.0754	1					
Departure Weekdays	0.1500	-0.0023	0.0235	-0.0070	-0.0138	-0.0819	1				
Peak Hours	0.0811	0.0890	-0.0330	0.0195	-0.1053	0.0431	-0.0159	1			
Summer	0.0386	0.1556	-0.0058	-0.0104	0.0014	0.0338	0.0241	-0.0352	1		
Relative MS	0.0105	-0.0885	-0.0183	-0.0315	0.0038	-0.0103	-0.0065	0.0739	-0.0215	1	
Eligible Alternatives	0.1020	-0.0461	-0.0392	-0.0180	-0.1377	-0.0475	-0.0029	0.0870	0.0234	0.2358	1

Appendix 4: Leisure index

Salanti et al. (2012) first introduced the leisure index to distinguish between leisure- and business- oriented route according to the pricing strategy the airlines apply. In details, this index is based on the idea that carriers, especially LCCs, undertake intertemporal price discrimination to offer different prices to high yield business passengers, who are known to have a higher willingness to pay and to buy flight tickets a few days before departure, and leisure ones, who are greatly price sensitive and tend to book in advance (Salanti et al., 2012). In markets where airlines chose to strongly implement such kind of discrimination, there is strong increase in fares in the last 15 days prior to departure with respect to previous days. In other words, 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.

The leisure index is defined as follows:

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

with $\beta_{1\text{-}90,i}$ and $\beta_{1\text{-}15,i}$ as the dynamic price indicators computed over 90 and 15 days of advance, respectively, per each flight i of route r, which are calculated based on the simplest airfare formula in Malighetti et al. (2009):

$$P_{irt} = \frac{1}{\alpha_{ir}(1+\beta_{ir}\cdot t)} \quad \text{(A.2)}$$

where $P_{irt}$is the price for a seat offered t days in advance for flight i on route r, and $\alpha_{ir}$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 days to departure, while a high β_{ir} corresponds to a greatly significant discounted fare on advance bookings.

A greatly negative leisure index L_r means that, a few days before departure, fares tend to be higher than what is expected by considering the overall trend, thus suggesting that during the last 15 days, airlines aim to address consumers with a higher willingness to pay, i.e. business passengers (Salanti et al., 2012). As a consequence, the more the leisure index is negative, the more the route can be defined as a 'business-oriented route'. In these terms, the sample presents a large heterogeneity of markets. The Milan Malpensa destination (MXP) has the most negative leisure index in the sample, equal to -0.067 and presents a quite steady pattern until two weeks to departure. While the average price for the AMS-MXP route is €96, during the last 15 days, the price trend assumes the classical shape of a J-curve, typical of intertemporal price discrimination (Bergantino and Capozza, 2015), ranging from €98 to €155. Oppositely, Split (SPU) has a leisure index of -0.024, thus still suggesting an increase in price dynamicity during the last days to departure, but with a less steep increasing trend. Indeed, Figure A.2 shows a steady price pattern for the Split market, with an average fare equal to €130 for all the booking period, varying from €124 to €141 from 15 to 1 days to departure, respectively.

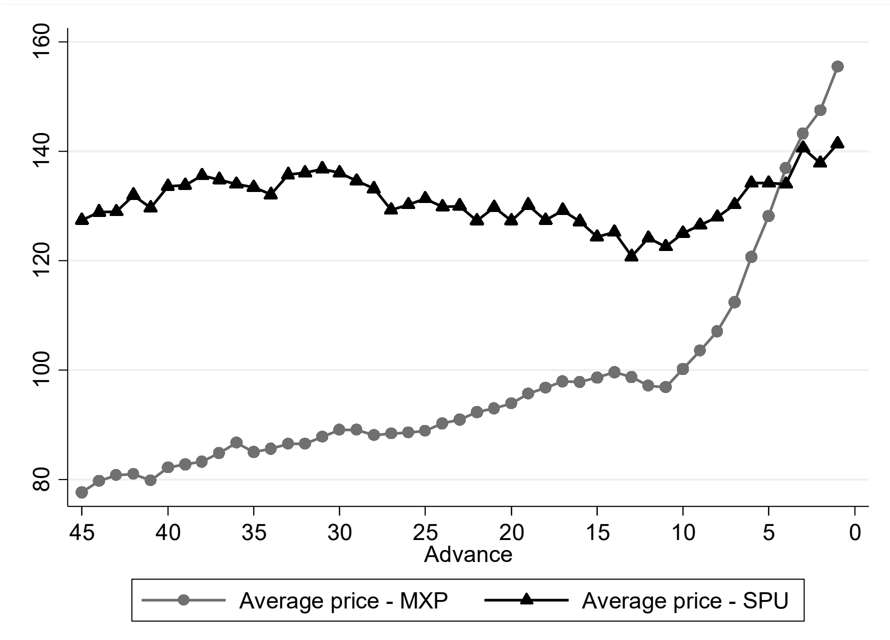

Figure A.2– Average price trends of a leisure- (SPU) and a business- (MXP) oriented route

Appendix 5: Multi-dimensional price elasticity values without correcting for endogeneity

As shown in Table 4.1, OLS and 2SLS regression results are similar, with a more negative price coefficient in the 2SLS model than in the OLS model. Without instrumenting price, overall price elasticity of demand results to be lower in absolute value, equal to -0.552. This indicates that a 1% increase in the price generates a 0.6% decrease in the demand for air travel. By investigating price elasticity changes with respect to different dimensions, overall values are lower, but there is still an interesting difference to be explored.

Figure A.3 depicts the elasticity values with respect to booking days. As the departure date approaches, the price elasticity of demand ranges from -1.498 to a minimum of -0.466 four days before departure. Differently from the 2SLS results (see Section 3.3.2 for further details), air travel demand dynamically changes from being elastic to being rigid three weeks before departure, between the 20th and 19th day. Even if there is a discrepancy of around a week, this result is consistent with the one in Section 3.3.2 and with previous literature (e.g., Mumbower et al., 2014), where the elasticity decreases as departure day approaches.

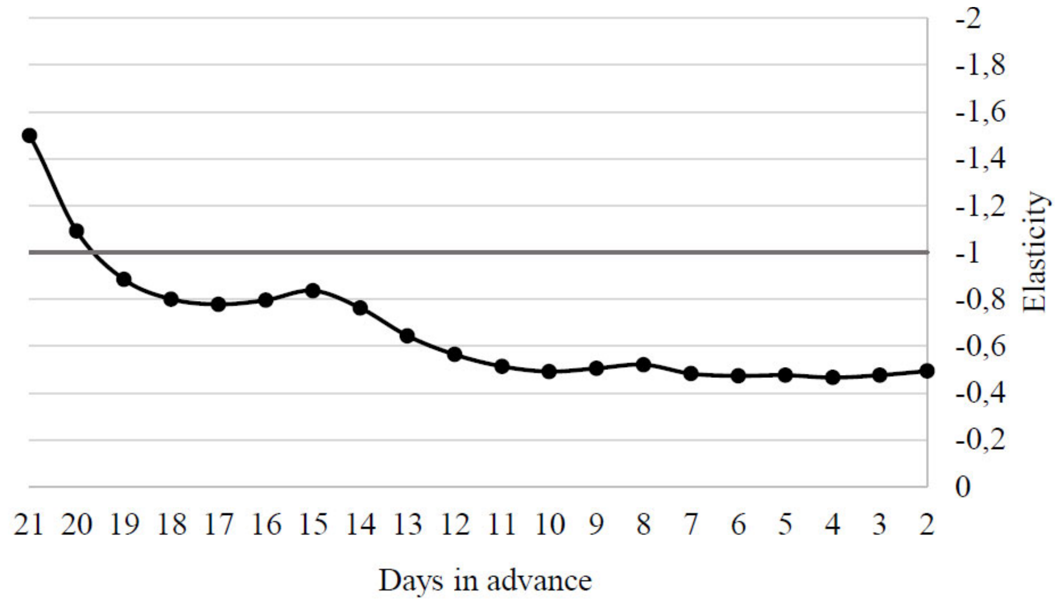

Figure A.3 - Price elasticity values by days in advance
Notes: All elasticity values are significant at the <0.1% level
The ANOVA F-statistic (43) is 26.76, significant at the <0.1% level

For what concerns price elasticity changes with respect to booking day of the week, Table A.8 shows elasticity increases gradually from Mondays (-0.450) to Fridays (-0.521). During weekends, passengers are slightly more sensitive (the price elasticity of demand reaches the value of -0.957 and -0.847 during Saturdays and Sundays, respectively). Similarly to Section 3.3.2, this result is in accordance with previous literature stating that leisure passengers, acknowledged to be more price sensitive, tend to book during weekends (Mantin and Koo, 2010; Mumbower et al., 2014).

Table A.8 – Price elasticity values per booking day

Elasticities over the Booking Dimension	
Booking Day	
Working Days	-0.479
Monday	-0.450
Tuesday	-0.466
Wednesday	-0.471
Thursday	-0.489
Friday	-0.521
Weekends	-0.900
Saturday	-0.957
Sunday	-0.847
ANOVA F-statistic (6)	126.59***

Notes: All elasticity values are significant at the <0.1% level
**** indicates statistical significance at the 0.1% level*

Computing price elasticity values with respect to flight characteristics, it is possible to notice how passengers travelling during weekends and at lunchtime are more price sensitive than others (Table A.9). Consistently with results from Section 3.3.2, this outcome suggests how low-price sensitive passengers typically travel during working days and during morning hours, in accordance with the theory that LCCs tend to discriminate between leisure and high yield passengers according to time and date of departure (e.g., Salanti et al. 2012).

Table A.9 – Price elasticity values per departure day and departure hour

Elasticities over the Flight Dimension	
Departure Day	
Working Days	-0.774
Monday	-0.541
Tuesday	-0.406
Wednesday	-0.430
Thursday	-0.431
Friday	-0.512
Weekends	-0.471
Saturday	-0.681
Sunday	-0.831
ANOVA F-statistic (6)	356.38***
Departure Hour	
Morning	-0.505
Lunchtime	-0.619
Afternoon	-0.587
Evening	-0.560
ANOVA F-statistic (3)	150.82***

Notes: All elasticity values are significant at the <0.1% level
**** indicates statistical significance at the 0.1% level*

Table A.10 shows how the price elasticity changes with respect to the leisure or business orientation of a route. Price elasticity is found to vary from -1.406 for Split (SPU) to -0.393 for Hamburg (HAM). Routes where easyJet is the only operating carrier registers 11.5% less price elasticity estimates, with a value of -0.516).

Table A.10 – Price elasticity value per route with respect to the leisure/business route orientation

Elasticities over the Route Dimension		
Destination		
Leisure-oriented routes[a]		-0.681
	SPU	-1.406
	LIS	-0.944
	PRG	-0.863
	BRS	-0.791
	GLA	-0.708
	BFS	-0.691
	NCL	-0.691
	BOD	-0.671
	EDI	-0.668
	FCO	-0.586
	BSL	-0.548
	SEN	-0.540
	GVA	-0.503
Business oriented routes[a]		-0.478
	MAN	*-0.566*
	LPL	*-0.547*
	MXP	*-0.494*
	STN	*-0.484*
	LTN	*-0.425*
	LGW	*-0.422*
	SXF	*-0.417*
	HAM	*-0.393*
ANOVA F-statistic (20)		73.75***

Notes: All elasticity values are significant at the <0.1% level
**** indicates statistical significance at the 0.1% level*
[a] *Leisure- (business-) oriented routes are characterized by a leisure index higher (lower) than the average.*

Seasonality takes a role in price elasticity. Even if spring and summer are considered as very similar, it is registered a little variation in elasticity values. During summer months, it is found to be -0.565, while in spring months it is -0.543. By computing differences at the month level (Table A.11), the highest price elasticity occurs in the month of July (-0.594), followed by August (-0.586), May (-0.585), and April (-0.581).

Table A.11 – Price elasticity values per month

Elasticities over the Seasonal Dimension	
Spring	-0.543
March	-0.517
April	-0.581
May	-0.585
June	-0.497
Summer[a]	-0.565
July	-0.594
August	-0.586
September	-0.492
ANOVA F-statistic (6)	36.89***

Note: All elasticity values are significant at the <0.1% level
**** indicates statistical significance at the 0.1% level*
[a]Summer starts on 21 June

Combining seasonality with the other dimensions, there is a stronger evidence of the impact of seasonality on price elasticity (Table A.12). Across all dimensions, evidence shows that consumers are more price elastic during summer. For example, for reservations made more than 15 days in advance, price elasticity is found to be 6% higher during summer with respect to spring. Similarly, also booking days register a price elasticity from 3% to 8% higher during summer, for Sundays and Fridays, respectively. Interestingly, flights departing during Tuesdays and Thursdays register a 4% lower price elasticity during summer with respect to summer. Similarly, passengers travelling in the morning and in the evening during summer are less price elastic than in spring.

Table A.12 – Price elasticity values per season, days of advance, booking day, departure day, and 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	-0.471	-0.486
6-10 days	-0.483	-0.504
11-15 days	-0.613	-0.641
>15 days	-1.115	-1.187
ANOVA F-Statistic (4)	221.51***	
Booking Day		
Working Days	-0.466	-0.494
Monday	-0.436	-0.468
Tuesday	-0.455	-0.478
Wednesday	-0.457	-0.485
Thursday	-0.475	-0.510
Friday	-0.507	-0.546
Weekends	-0.888	-0.971
Saturday	-0.940	-0.861
Sunday	-0.837	-0.981
ANOVA F-Statistic (7)	125.34***	
Flight Dimension		
Departure Day		
Working Days	-0.462	-0.483
Monday	-0.522	-0.564
Tuesday	-0.414	-0.398
Wednesday	-0.415	-0.448
Thursday	-0.439	-0.420
Friday	-0.493	-0.536
Weekends	-0.761	-0.791
Saturday	-0.662	-0.705
Sunday	-0.821	-0.843
ANOVA F-Statistic (7)	318.90***	
Departure Hour		
Morning	-0.512	-0.497
Lunchtime	-0.508	-0.753
Afternoon	-0.569	-0.613
Evening	-0.566	-0.552
ANOVA F-Statistic (4)	86.17***	

Note: All elasticity values are significant at the <0.1% level
**** indicates statistical significance at the 0.1% level*

Table A.13 – Price elasticity values per season and route, 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	-0.608	-0.778	102	111	9%
BOD	-0.756	-0.582	92	93	1%
BRS	-0.804	-0.772	164	129	-21%
BSL	-0.574	-0.509	216	157	-27%
EDI	-0.539	-0.823	144	129	-10%
FCO	-0.611	-0.551	280	211	-25%
GLA	-0.524	-0.957	60	54	-10%
GVA	-0.520	-0.472	246	121	-51%
HAM	-0.458	-0.342	44	59	34%
LGW	-0.422	-0.423	484	425	-12%
LIS	-0.964	-0.923	45	40	-11%
LPL	-0.552	-0.541	199	172	-14%
LTN	-0.421	-0.429	366	328	-10%
MAN	-0.559	-0.572	187	175	-6%
MXP	-0.504	-0.478	384	287	-25%
NCL	-0.691		52		-
PRG	-0.964	-0.742	99	76	-23%
SEN	-0.537	-0.543	213	175	-18%
SPU	-0.786	-1.827	28	53	89%
STN	-0.476	-0.493	289	271	-6%
SXF	-0.409	-0.429	264	187	-29%
ANOVA F-Statistic (21)			73.98***		
<u>*LC Dominance*</u>					
<100%	-0.585	-0.580	2,113	1,669	-21%
100%	-0.491	-0.547	1,845	1,584	-14%
ANOVA F-Statistic (2)			125.60***		

Notes: All elasticity values are significant at the <0.1% level
**** indicates statistical significance at the 0.1% level*
[a] Flight variations are computed as the percentage difference between the number of summer and spring flights

Table A.13 shows price elasticity over the route and seasonal dimension. Routes that register a higher variation in price elasticity of demand are Split (+132% during summer), Glasgow (+82%), and Edinburgh (+53%), all considered as leisure-oriented routes according to the leisure index. Oppositely, Hamburg, Bordeaux, and Prague register from -23% to -25% price elasticity values during summer. This insight sheds light on the seasonal characteristics of routes and their degree of leisure-orientation, varying with seasonality, especially for routes with no significant variation in flight frequency (BOD). When looking at competition, destinations where easyJet is the only carrier offering flights present a 10% lower price elasticity in spring with respect to summer, while routes suffering from competition have a quasi-stable price elasticity, equal to -0.585 in spring and -0.580 in summer.

Appendix 6: 2SLS regression with different values of θ

Table A.14 - 2SLS regression estimates on demand at different values of θ

Variables	$\theta = 0.2$	$\theta = 0.4$	$\theta = 0.6$	$\theta = 0.8$
Price	-0.0101***	-0.0101***	-0.0101***	-0.0101***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Price Drop	0.0968*	0.0981*	0.0986*	0.0983*
	(0.0417)	(0.0417)	(0.0416)	(0.0416)
	[0.0203]	[0.0203]	[0.0186]	[0.0179]
PVNAP	-1.2528**	-1.8822***	-2.9648***	-5.7370***
	(0.3860)	(0.4940)	(0.6827)	(1.1596)
	[0.0012]	[0.0012]	[0.0001]	[0.0000]
Advance	-0.0720***	-0.0720***	-0.0721***	-0.0723***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Booking Weekdays	0.8068***	0.8067***	0.8068***	0.8070***
	(0.0205)	(0.0205)	(0.0205)	(0.0205)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Departure Weekdays	0.2949***	0.2949***	0.2945***	0.2931***
	(0.0232)	(0.0232)	(0.0232)	(0.0232)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Peak Hours	0.2378***	0.2379***	0.2381***	0.2383***
	(0.0245)	(0.0245)	(0.0245)	(0.0245)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Summer	0.3298***	0.3300***	0.3301***	0.3301***
	(0.0227)	(0.0226)	(0.0226)	(0.0226)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Relative MS	0.7872***	0.7879***	0.7877***	0.7834***
	(0.1449)	(0.1449)	(0.1449)	(0.1449)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Eligible Alternatives	-0.0758***	-0.0761***	-0.0762***	-0.0762***
	(0.0127)	(0.0127)	(0.0127)	(0.0127)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Constant	3.3019***	3.3070***	3.3151***	3.3318***
	(0.1354)	(0.1353)	(0.1351)	(0.1348)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Observations	58,354	58,354	58,354	58,354
F-statistic	259.37	259.83	260.26	260.66

*Note: ***, **, *, and + indicate significance at the less than 0.1%, 1%, 5%, and 10% levels, respectively. Standard errors in parenthesis and P-values in squared brackets*

Table A.14 shows the complete 2SLS regressions at different values of θ. Interestingly, all the independent variables present almost constant values across the different weights assigned to past price fluctuations. The only exception is given by the coefficient of PVNAP, which, as shown in Table 5.5, increases with θ, thus suggesting that the analysis fully captures of the impact of price volatility on demand.

Appendix 7: OLS and 2SLS regression results with alternative instrumental variables

Table A.15 shows the result of 2SLS regression in case the instrumental variable is represented by the average price on similar routes with respect to the distance. To identify similar routes, they are aggregated according to the distance, generating three categorical classes: between 300 km and 550 km, between 551 km and 800 km, and more than 800 km. Afterwards, for each route m, the average price on routes n-m that are in the same class route m is computed. The average price of the routes n-m, computed t days in advance represents the instrumental variable for the price on route n on the date d during the t^{th} day before departure. Results are significantly consistent with respect to the ones in Table A.14.

Similar conclusions can by drawn from Table A.16, which illustrates outcomes of the 2SLS regressions with different values of θ when the instrumental variable is the price lag, computed as the airfare for the same flight a week before, with the same booking days left.

Table A.15 - 2SLS regression estimates on demand at different values of θ *when the instrumental variable is the average price on similar routes with respect to distance*

Variables	$\theta = 0.2$	$\theta = 0.4$	$\theta = 0.6$	$\theta = 0.8$
Price	-0.0075***	-0.0075***	-0.0075***	-0.0075***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Price Drop	0.1294**	0.1307**	0.1311**	0.1305**
	(0.0414)	(0.0414)	(0.0413)	(0.0413)
	[0.0018]	[0.0016]	[0.0015]	[0.0016]
PVNAP	-1.6047***	-2.3553***	-3.6375***	-6.8785***
	(0.3820)	(0.4882)	(0.6742)	(1.1455)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Advance	-0.0727***	-0.0727***	-0.0728***	-0.0731***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Booking Weekdays	0.8107***	0.8107***	0.8108***	0.8111***
	(0.0205)	(0.0205)	(0.0205)	(0.0205)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Departure Weekdays	0.3332***	0.3332***	0.3328***	0.3314***
	(0.0223)	(0.0223)	(0.0223)	(0.0223)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Peak Hours	0.2044***	0.2046***	0.2046***	0.2047***
	(0.0239)	(0.0239)	(0.0239)	(0.0239)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Summer	0.2935***	0.2936***	0.2937***	0.2934***
	(0.0218)	(0.0218)	(0.0218)	(0.0218)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Relative MS	0.8510***	0.8521***	0.8519***	0.8470***
	(0.1448)	(0.1448)	(0.1448)	(0.1447)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Eligible Alternatives	-0.0759***	-0.0762***	-0.0764***	-0.0764***
	(0.0128)	(0.0128)	(0.0128)	(0.0128)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Constant	2.9683***	2.9735***	2.9819***	2.9994***
	(0.1227)	(0.1226)	(0.1225)	(0.1224)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Observations	58,354	58,354	58,354	58,354
F-statistic	258.21	258.66	259.07	259.44

*Note: ***, **, *, and + indicate significance at the less than 0.1%, 1%, 5%, and 10% levels, respectively. Standard errors in parenthesis and P-values in squared brackets*

Table A.16 - 2SLS regression estimates on demand at different values of θ *when the instrumental variable is the one-week lagged price*

Variables	$\theta = 0.2$	$\theta = 0.4$	$\theta = 0.6$	$\theta = 0.8$
Price	-0.0088***	-0.0088***	-0.0088***	-0.0088***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Price Drop	0.0862+	0.0873+	0.0877+	0.0873+
	(0.0472)	(0.0471)	(0.0471)	(0.0471)
	[0.0677]	[0.0641]	[0.0628]	[0.0635]
PVNAP	-1.3659***	-2.0088***	-3.1044***	-5.8682***
	(0.4139)	(0.5289)	(0.7305)	(1.2472)
	[0.0010]	[0.0001]	[0.0000]	[0.0000]
Advance	-0.0726***	-0.0726***	-0.0727***	-0.0729***
	(0.0020)	(0.0020)	(0.0020)	(0.0020)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Booking Weekdays	0.7945***	0.7945***	0.7947***	0.7951***
	(0.0232)	(0.0232)	(0.0232)	(0.0232)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Departure Weekdays	0.3041***	0.3042***	0.3040***	0.3030***
	(0.0258)	(0.0258)	(0.0258)	(0.0258)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Peak Hours	0.2212***	0.2214***	0.2214***	0.2211***
	(0.0279)	(0.0279)	(0.0279)	(0.0279)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Summer	0.3299***	0.3300***	0.3301***	0.3299***
	(0.0256)	(0.0256)	(0.0256)	(0.0256)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Relative MS	0.9845***	0.9853***	0.9854***	0.9826***
	(0.1631)	(0.1631)	(0.1631)	(0.1630)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Eligible Alternatives	-0.0832***	-0.0834***	-0.0836***	-0.0835***
	(0.0143)	(0.0143)	(0.0143)	(0.0143)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Constant	3.0339***	3.0380***	3.0441***	3.0561***
	(0.1480)	(0.1479)	(0.1478)	(0.1476)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Observations	58,354	58,354	58,354	58,354
F-statistic	205.09	205.40	205.67	205.89

*Note: ***, **, *, and + indicate significance at the less than 0.1%, 1%, 5%, and 10% levels, respectively. Standard errors in parenthesis and P-values in squared brackets*

Appendix 8 : Regression results with PVOLN

Figure A.4 shows the trend of price volatility over time. Consistently with PVNAP, price volatility increases over time. Even if it is not surprising given that $\mathrm{PVOLN}_{\mathrm{irdT}} = 0$, it is interesting to notice how price volatility differs with respect to the considered market, where the maximum value varies from 0.015 for Split to 0.042 for Berlin.

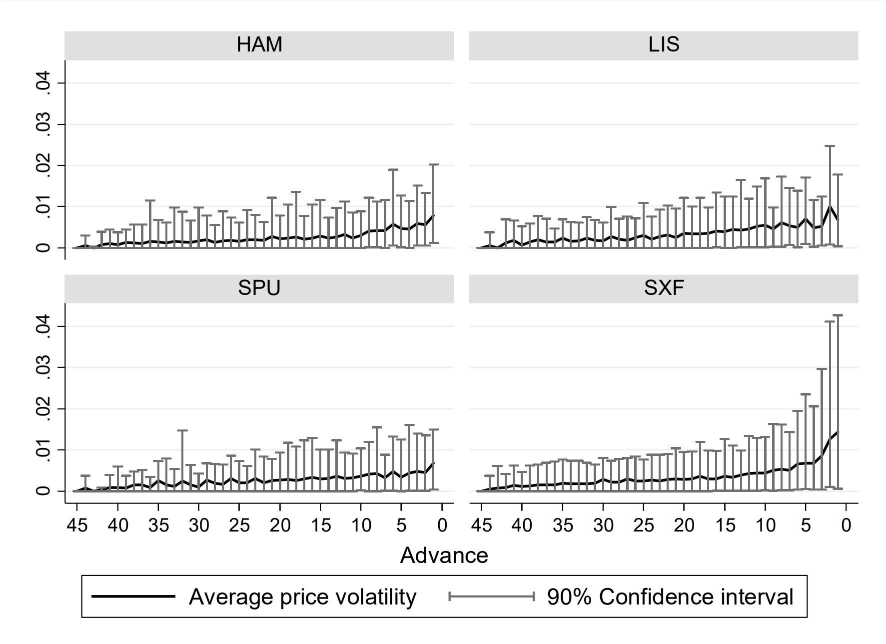

Figure A.4 - Average PVOLN *with* $\theta = 0.8$ *over days of advance for AMS-HAM, AMS-LIS, AMS-SPU, and AMS-SXF*

Table A.17 and Table A.18 show the outcomes of the regression with the use of $PVOLN$ instead of $PVNAP$. Results are similar and consistent across all the variables included.

Table A.17 – OLS and 2SLS regression estimates on demand with PVOLN

Variables	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
Price	-0.0118***	-0.0120***	-0.0103***	-0.0113***
	(0.0002)	(0.0003)	(0.0006)	(0.0009)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Price Drop	0.0888*	0.1323*	0.1066**	0.1410**
	(0.0391)	(0.0531)	(0.0397)	(0.0526)
	[0.0231]	[0.0127]	[0.0073]	[0.0074]
PVOLN		-4.0243***		-4.2787***
		(0.8517)		(1.0538)
		[0.0000]		[0.0000]
Advance	-0.0718***	-0.0704***	-0.0721***	-0.0707***
	(0.0014)	(0.0018)	(0.0017)	(0.0021)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Booking	0.8243***	0.8157***	0.8251***	0.8142***
Weekdays	(0.0194)	(0.0266)	(0.0192)	(0.0261)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Departure	0.2437***	0.2272***	0.2648***	0.2367***
Weekdays	(0.0203)	(0.0284)	(0.0217)	(0.0297)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Peak Hours	0.2572***	0.2964***	0.2381***	0.2871***
	(0.0216)	(0.0294)	(0.0229)	(0.0310)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Summer	0.2994***	0.5551***	0.2805***	0.5433***
	(0.0198)	(0.0318)	(0.0211)	(0.0334)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Relative MS	0.6321***	1.2587***	0.6655***	1.2203***
	(0.1358)	(0.2253)	(0.1310)	(0.2120)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Eligible	-0.0601***	-0.0884***	-0.0601***	-0.0862***
Alternatives	(0.0120)	(0.0202)	(0.0115)	(0.0190)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Constant	3.5474***	3.0491***	3.3590***	2.9969***
	(0.1041)	(0.1590)	(0.1285)	(0.1740)
	[0.0000]	[0.0000]	[0.0000]	[0.0000]
Observations	58,354	58,354	58,354	58,354
R-squared	0.135	-	0.134	-
F-statistic	370.92	201.43	303.62	165.53

*Note: ***, **, *, and + indicate significance at the less than 0.1%, 1%, 5%, and 10% levels, respectively. Standard errors in parenthesis and P-values in squared brackets. Hausman test value is 0.81, suggesting there is no endogeneity*

Even from a price elasticity perspective, the values present a little variation, but trends are consistent along theta values. Overall, price elasticity at mean prices is equal to -0.579. In Figure A.5 details about elasticities for different deciles of price volatility are shown.

Table A.18– θ coefficients of the OLS and 2SLS regression estimates on demand with PVOLN

θ	(1) OLS			(2) 2SLS		
	Coefficient	St. Error	P-Value	Coefficient	St. Error	P-Value
0.1	-0.3711	(0.2336)	0.1122	-0.4490	(0.2947)	0.1276
0.2	-0.5054+	(0.2617)	0.0535	-0.5939+	(0.3298)	0.0717
0.3	-0.6789*	(0.2971)	0.0223	-0.7800*	(0.3729)	0.0365
0.4	-0.9106**	(0.3428)	0.0079	-1.0269*	(0.4277)	0.0164
0.5	-1.2350**	(0.4042)	0.0022	-1.3703**	(0.5008)	0.0062
0.6	-1.7198***	(0.4908)	0.0005	-1.8803**	(0.6042)	0.0019
0.7	-2.5158***	(0.6231)	0.0001	-2.7120***	(0.7647)	0.0004
0.8	-4.0243***	(0.8517)	0.0000	-4.2787***	(1.0538)	0.0000
0.9	-7.9436***	(1.3948)	0.0000	-8.3345***	(1.7796)	0.0000

*Note: ***, **, *, and + indicate significance at the less than 0.1%, 1%, 5%, and 10% levels, respectively.*

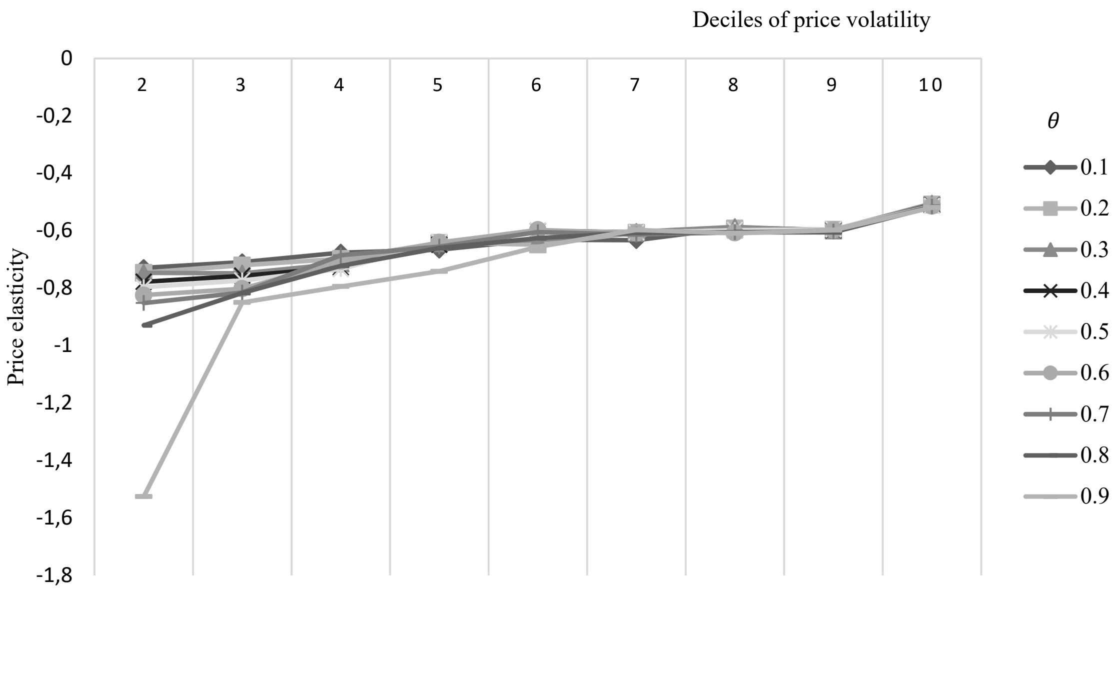

Figure A.5 - Price elasticity according to the different levels of price volatility (PVOLN)