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Research paper

Quantifying an Airline's brand Image: The Ryanair disutility effect

Christos Evangelinos [a,*], Stefan Tscharaktschiew [b], Andy Obermeyer [b]

[a] IU International University of Applied Sciences, Germany, Campus Berlin, Frankfurter Allee 73A, 10247, Berlin, Germany
[b] Technische Universität Dresden, Faculty of Traffic Sciences "Friedrich List", Institute of Transport & Economics, 01062, Dresden, Germany

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ABSTRACT

This paper supports the hypothesis that airline brand image might seriously impact passenger booking behavior. To offset the disadvantage associated with a negative image, an airline will need to decrease ticket prices. Thus, airline brand name reputation can be monetized and translated into airline revenue loss.

We use data from a choice experiment in which 336 passengers from Germany choose out of two airlines, one of which is always Ryanair. The approach employs choice modeling techniques (including mixed logit) and utilizes Ryanair-specific variables to assess their impact on airline choice probability.

Results indicate that the higher the passengers' income, the lower the choice probability for Ryanair. Results are used to compute the required price reduction to render passengers indifferent to both alternatives and term this "the disutility effect". Additional computations reveal the potential for airlines to increase revenues by improving their reputation and eliminating operational functions that may lead to a detrimental brand image.

1. Introduction

It is conventional wisdom in business and economics that a firm's good reputation goes along with higher activity and profits. In particular for the airline industry, airline service quality might be seen as a credible commitment to passengers to perform the transportation service at the "promised" level. One would then expect that passengers consider past negative experiences in perceived quality in their booking intentions or even utilize information from print media. Thus, an airline's perceived and public image might influence future passenger volumes.

Several approaches show that a firm's reputation is closely associated with the ability to increase revenues (see, e.g., Ailawadi et al., 2003; Sattler et al., 2010 for general treatments, or e.g. Bronnenberg et al., 2015 for the pharmaceutical industry as examples). Whereas markups (respectively discounts) due to brand image reputation are intensively discussed in the literature, the quantification and monetization of brand image reputation in individual airline choice behavior is rather underrepresented and mainly restricted to the individual valuation of single quality airline attributes (see next section for a review) or to factors contributing to brand image (Bougoure et al., 2016; Chen & Chang, 2008; Osaki & Kubota, 2016; Prentice et al., 2019). In addition, some studies discussing pricing and competition issues identify a mixture of hub and brand premiums at hub airports within price discrimination schemes (see e.g. Alderighi et al., 2011).

This issue is closely related to airline service quality measurement. In measuring airline service quality, several approaches identify and synthesize the dimensions and attributes contributing to airline service quality in a single index (e.g., Parasuraman et al., 1985, 1988; Percin, 2018). In addition, other analyses employ passenger surveys (Bellizzi et al., 2020) or fuzzy model approaches (Liou & Tzeng, 2007) to assess airline quality and passenger satisfaction. Furthermore, some studies emphasize the interrelation between airline and airport service quality for passenger satisfaction and use structural equation approaches (e.g. Farooq et al., 2018) or combine them with ordered probit analyses (Allen et al., 2020) in order to address the complexity of this issue, in particular the influence of latent variables in airline perceived quality.[1] Finally, choice modeling approaches have been widely applied (e.g. Espino et al., 2008; see next section) to determine the individual valuation of single airline quality attributes. With regard to the impact of airline quality, several contributions demonstrate the importance of perceived quality for passenger satisfaction (Shen & Yahya, 2021; Shah et al., 2020) or for loyalty (Shen & Yahya, 2021; Chonsolasin et al., 2021) and repurchase intentions (Chen et al., 2019; Shah et al., 2020).

There can be no doubt that the perceived service quality of an airline

* Corresponding author.
E-mail addresses: christos.evangelinos@iu.org (C. Evangelinos), stefan.tscharaktschiew@tu-dresden.de (S. Tscharaktschiew), andy.obermeyer@tu-dresden.de (A. Obermeyer).

[1] An in-depth overview of airline quality assessment is provided by Eboli et al. (2022).

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contributes to its brand image (see discussion in the literature review). Nevertheless, it is not the purpose of this paper to assess the impact of airline quality on the dimensions of passenger satisfaction, loyalty, and repurchase intentions. Instead, the focus is on how the airline's image influences individual passenger booking decisions. In other words, the present study explores the impact of airline reputation on passenger choices. It is therefore necessary to consider the brand name of an airline in its entirety.

In addition, the airline's ability to influence passenger volumes and augment its revenues through the enhancement of its public image is also a subject of interest. Passengers attaching a higher value to airline brand name will expectedly have a willingness to pay for this. Airlines may then utilize such information and consider their good reputation in setting appropriate ticket prices. Conversely, revenue management for airlines with a low image will also be influenced accordingly. It is therefore likely that such airlines will possibly need to lower their fares in order to offset this and attract a greater number of passengers. Such pricing behavior will be of particular importance for connections with a high degree of competition, whereas for connections with sufficient market power, there might be at first no need to lower fares. Nevertheless, even for such market segments a low reputation might lead in the long run to increased market entries by competitors (given sufficient market contestability). It is therefore possible that in the long run a low brand reputation might be seen by potential competitors as a signal for market contestability.

The present paper is therefore concerned with the quantification of the impact of airline brand image on passengers' choice behavior. This will facilitate the demonstration of the financial potential of an airline to increase its revenues if it polishes its own reputation. A choice experiment with an orthogonal design was employed and 336 passengers from Germany were surveyed in order to test this hypothesis for the case of Ryanair. This airline appears to be a suitable case study, as it is one of Europe's major Low-Cost Carriers (LCC) and has previously encountered persistent negative media attention, including consecutive years of achieving the lowest rankings in passenger satisfaction surveys in the UK (BBC, 2019; The Irish Times, 2019; Fernandez, 2024; ftnNews, 2024), allegations regarding low wages and substandard working conditions (Daily Mail, 2017; The Guardian, 2018), or even concerns about carelessness for passengers (Focus, 2019). In the context of the monetization of the brand image, the paper employs the term "disutility effect".

Concerning the case of Ryanair, the paper starts with a first tentative analysis of real market data. This represents a first intermediate step in order to gain a first impression of whether the results of the subsequent modeling approach could be also documented in observed airline pricing behavior. By use of APEX fare data (see APEX, 2024) Figs. 1 and 2 illustrate and contrast the average yield per passenger for the four major European low-cost-carriers (Ryanair, easyJet, Eurowings and Norwegian) for the period 2015–2023 with that of Ryanair. This is done for

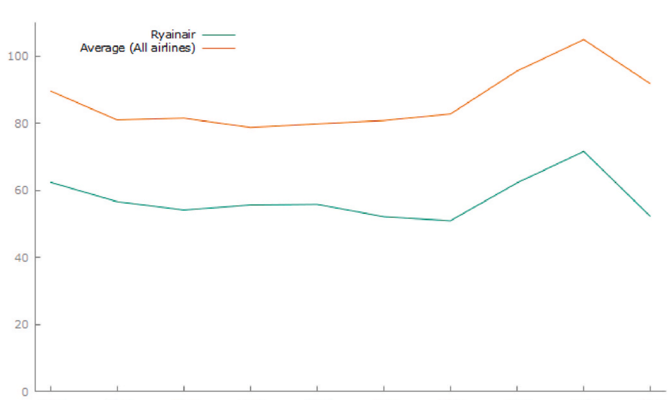

Fig. 1. Absolute average development of per passenger yields. Source: Own depiction based on APEX (2024) data.

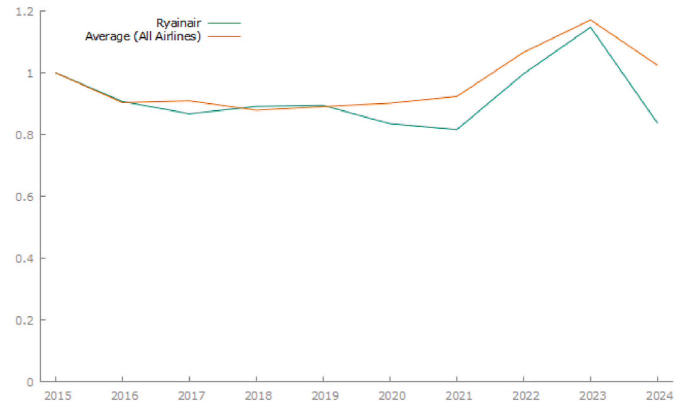

Fig. 2. Index based development of per passenger yields. Source: Own depiction based on APEX (2024) data.

both absolute values but also as a chain index in order to be able to assess the development over time. The average yield per passenger is solely based on (pure) ticket prices, thus leaving aside all revenues from ancillary services.

As Fig. 1 shows, Ryanair has consistently underperformed its competitors. The difference of Ryanair's per passenger yield to the entire group of major Low-Cost-Carriers' (including Ryanair itself) ranges between € 24 to € 39. In addition, Fig. 2 points out that this difference seems to increase over time. Certainly, such differences may be attributed to several reasons. Notably, the airlines might engage in different submarkets with a different degree of competition and also fly a different stage length. In addition, different regional submarkets[2] can also be a source for such results. Also, airline strategic decisions on price leadership or even inefficient revenue management could contribute to such results. In particular, the observed differences in yields may occur due to a lower cost structure by Ryanair, which would allow the airline to offer ticket prices also for passengers with a lower willingness to pay. For this reason, we use the same data sources to compute the cost per available seat kilometer (CASK) as well as its development. Figs. 3 and 4 show the results. Indeed, as illustrated in Fig. 3, Ryanair is the uncontested cost leader in the industry, as its CASK remains below the average of the competitors. However, Fig. 4 reveals that the CASK development by Ryanair although it remains below the one of the competitors (apart

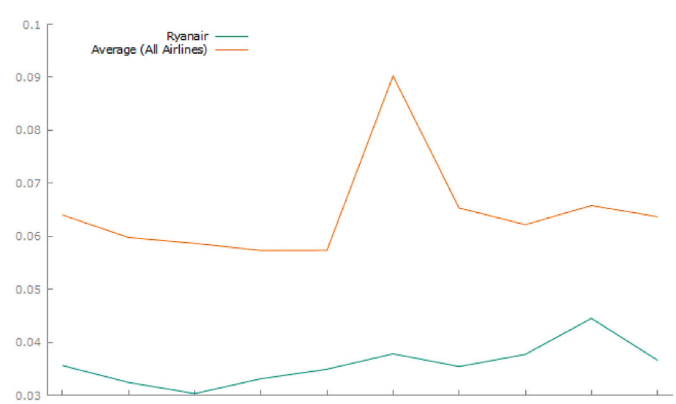

Fig. 3. Cost per Available Seat Kilometer. Source: Own depiction based on APEX (2024) data.

[2] For example, an airline could possibly serve predominantly markets in countries with lower average passenger income.

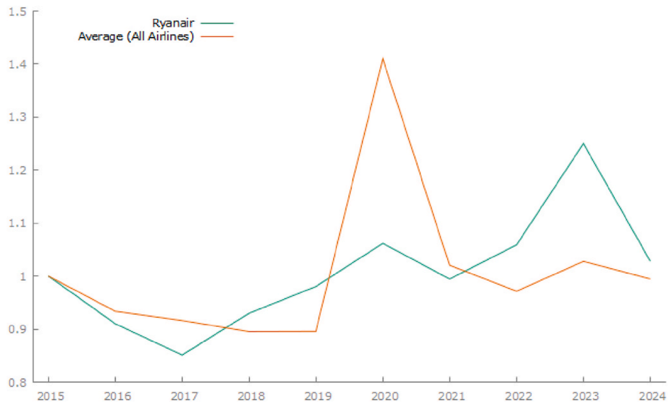

Fig. 4. Index based development of Cost per Available Seat Kilometer. Source: Own depiction based on APEX (2024) data.

during the COVID crisis), is slightly increasing. It thus seems that the airline faces difficulties to translate the increasing cost in corresponding yields over time, at least not at the same extent as the competitors. One possible explanation in this respect might be the disutility effect addressed in this paper. Here, it is hypothesized that the disutility effect resulting from a negative brand image might also be responsible for some parts of this observation. This suggests that even if revenue management performs efficiently, it would not be possible for an airline with a poor reputation to price at similar levels as its competitors. In this case, this phenomenon would be observable in the airline choice behavior by passengers.

The paper is organized as follows: Section 2 provides a review of itinerary choices focusing on quality elements of airline supply. Section 3 shows the modeling approach, describes the choice experiment, and discusses the data. Section 4 presents the results and discusses the implications. Finally, Section 5 concludes.

2. Literature review

Talking about airline brand image, it would be useful for the scope of this paper to clarify this term. Many studies use the notion of brand equity as a general term to describe the additional utility (or in the context of this paper, the disutility) associated with the brand name of a product. Several approaches differentiate in this respect between brand image, brand awareness perceived quality and brand loyalty as the main factors contributing to brand equity (Chen & Chang, 2008; Chen & Tseng, 2010), thus indicating, that brand equity goes beyond perceived airline quality. Most contributions use only one of these dimensions in their analysis and try to link brand related issues to passenger satisfaction and brand loyalty. This literature suggests that perceived airline service quality and passenger expectations on quality form brand equity (Jeeradist et al., 2016) and influence positively brand loyalty (Koech et al., 2023; Vuong et al., 2024), customer satisfaction (Akamavi et al., 2015; Hameed et al., 2024; Hussain et al., 2015; Pabla & Soch, 2023) and repurchase intentions (Koech et al., 2023; Prentice et al., 2019; Yang et al., 2012; Chen & Tseng, 2010; Chen & Chang, 2008; Chang & Sun, 2012). Some of the contributions underline the importance of brand reputation in instances of service failure (Sengupta et al., 2015). Specifically, these contributions highlight the pivotal role of brand credibility in facilitating recovery following a service failure (Bougoure et al., 2016). Interestingly, some studies show how airline credible commitment to environmental protection forms airline brand image and influences consumer behavior (e.g. Cavero-Rubio & Gonzalez-Morales, 2025). In addition, some studies discuss contributors to brand equity from the passenger-psychological perspective (Dirsehan & Kurtulus, 2018; Prentice et al., 2019) thus identifying individual factors like sensory, affective behavioral and intellectual ones as being important for brand experience and thus brand equity. The majority of the reviewed studies employ a survey and a structural equation model, in which brand equity contributors are mostly treated as mediators. Most importantly, one may conclude that all studies on brand equity consistently underline its direct or indirect importance for passenger choices, thus justifying the adopted approach in this paper. While past literature on airline image is rather interested in showing the interrelations and the importance of brand equity for airline success, approaches to quantify and, in particular, to monetize brand equity are rather rare. This paper uses therefore different modeling instruments to analyze the role of airline brand equity in passenger booking decisions and the corresponding monetary value passengers attach to it. Such results can be obtained by adopting discrete choice analysis.

Discrete choice analysis is a standard instrument in transport economics, including aviation. The main focus in aviation is the combined airline/airport choice by passengers (e.g. Evangelinos et al., 2021; Hess & Polak, 2005, 2006; Ishii et al., 2009; Pels et al., 2003, 2009, 2010).[3] This type of literature utilizes the trade-off between access time to the airport and flying cost. Additionally, variables like flight frequency (or scheduled delay), time of arrival, flying time, or delays enter these models, alongside sociodemographic passenger attributes. In general, it is found that leisure passengers react sensitively to fares, in contrast to business passengers, who are more sensitive to access times and flight frequencies.

In addition, several analyses concentrate on the (pure) airline choice behavior (henceforth itinerary choice). Such approaches offer a wide range for the analysis of several research questions. In many cases, scholars are interested in deriving elasticities and willingness-to-pay (WtP) values for the airline quality parameters, like frequent flyer programs, or extra legroom etc., or finding out how passengers respond to delays, types of aircraft, etc. Most contributions perform stated preference analysis and estimate Logit-type models (Multinomial Logit - MNL, Nested Logit – NL, Mixed Logit – ML). Table 1 provides an overview of the corresponding studies.

Table 1 illustrates that scholars follow a wide range of research questions in analyzing itinerary choices. In general, one may conclude that studies using revealed choices have more interest in forecasting airline demand (Coldren et al., 2003; Coldren & Koppelman, 2005; Lurkin et al., 2017). Conversely, studies with stated choices focus on the individual valuation of single airline attributes.

Concerning the latter, studies with latent class models are interested in addressing differences in the individual valuation of flight and airline attributes by using passenger subgroups according to individual characteristics (Caussade & Hess, 2009; Wen & Lai, 2010; Seelhorst & Liu, 2015; Morlotti et al., 2023; Moleman et al., 2024). In contrast, mixed logit approaches address passengers' preference heterogeneity with random coefficients drawn from an a-priori defined distribution (Caussade & Hess, 2009; Espino et al., 2008; Freund-Feinstein & Bekhor, 2017; Morlotti et al., 2023; Warburg et al., 2006). In general, the majority of studies pay attention to times, connectivity issues and delays (McCandless, 2024), while competition issues in form of code-sharing are considered by Coldren and Koppelman (2005) and Lurkin et al. (2017). All stated choice studies use the trade-off between fares and quality attributes. In many approaches frequent flyer programs are part of the choice experiment. In general, one may conclude that high frequencies, meals onboard, extra legroom, luggage, in-flight entertainment, direct flights, seat reservation, and participation in a frequent flyer program influence, as expected, passenger choices positively. All these approaches offer valuable insights into the individual valuation of single quality elements of airlines.

Given the scope of this paper to analyze airline image in its entirety, the studies by Milioti et al. (2015), Proussaloglou and Koppelman (1999), and Warburg et al. (2006) are of particular relevance. They all

[3] An in-depth literature review is provided by Fukushi et al. (2024).

Table 1
Major studies in itinerary choices.

Paper	Modeling approach	Data	Main quality elements considered
Balcombe et al. (2009)	ML	Stated choice experiment with fractional orthogonal design and 568 responses	Seat pitch and width, in-flight entertainment, in-flight meal, complimentary drinks
Cantillo et al. (2021)	MNL and NL	Revealed choices of 876 passengers for Medellin Airport-Colombia	Influence of departure time, different payer, schedule delay
Caussade and Hess (2009)	MNL, ML and latent class models	Stated choice experiment with fractional orthogonal design and 915 respondents	Frequent flyer programs, ticket cancellation, seat reservation, reservation changes
Chang and Sun (2012)	MNL	Stated choice experiment with fractional factorial design and 286 respondents	Flight frequency, luggage restrictions, destination airport
Espino et al. (2008)	MNL and ML	Stated choice experiment with fractional factorial design and 310 respondents	Comfort, frequency reliability, reservation changes, free food
Coldren and Koppelman (2005)	NL	Revealed itinerary choice for 469,078 passengers from CRS bookings	Aircraft type, code sharing, level of service, departure time
Lurkin et al. (2017)	MNL with instrumental variables and bootstrapping	Revealed itinerary choice for more than 3 million passengers from Airlines Reporting Corporation	Aircraft type, elapsed time, departure time, direct flight, code sharing
Martin et al. (2011)	MNL	Stated itinerary choices with fractional factorial design and 310 respondents	Penalties for booking changes, food, legroom, frequency, reliability, frequent flyer programs
Milioti et al. (2015)	Multivariate Probit	Revealed itinerary choices from 853 passengers	Airline image, frequent flyer programs, reliability, and safety, served network, in-flight entertainment, friendly and helpful staff
Proussaloglou and Koppelman (1999)	MNL	Stated choices from 908 passengers	Quality of service, schedule time difference, frequent flyer programs, market presence of the carrier
Warburg et al. (2006)	MNL and ML	Combination of revealed and stated choices with experimental design for 118 passengers	Schedule time difference, flight time, on-time performance, inertia, number of stopovers
Wen and Lai (2010)	MNL and latent class models	Stated choice with fractional orthogonal design and 322 respondents	Flight frequency, on-time performance, check-in service, cabin crew service, schedule time difference
Coldren et al. (2003)	MNL	Revealed itinerary choices for 2515 passengers	Level of service, connection quality, aircraft type, carrier, time of day
Freund-Feinstein and Bekhor (2017)	Mixed CNL	Stated choice with 914 respondents for different submarkets	Days until departure, legroom, cancellation fee, FFP, delays, connection time, personal entertainment
Morlotti et al. (2023)	Conditional Logit, ML and latent class choices	Stated choices with 245 respondents	Direct connection, flying time, connecting time, integrated transfer
Seelhorst and Liu (2015)	MNL and latent class choices	Stated choices with 830 respondents	Travel time, connections, type of aircraft, FFP arrival and departure times
Moleman et al. (2024)	Nested Logit and latent class choices	Stated choices with 1211 respondents and efficient choice design	Travel time, flight frequency, delay probability, connecting time direct flight

include variables that might directly or indirectly be attributed to the airline's image. Milioti et al. (2015) incorporate airline image directly in their research,[4] whereas Proussaloglou and Koppelman (1999) include the quality of service in form of passenger ratings. In addition, Warburg et al. (2006) incorporate an inertia variable to account for passenger reluctance to change airlines, which can also be regarded as an attribute accounting for airline image. An interesting result emerges also in the approach by Seelhorst and Liu (2015), wherein the authors find a passenger premium for Southwest (over the alternative specific constant). This paper can therefore be seen as an extension of the contributions by Milioti et al. (2015), Proussaloglou and Koppelman (1999), Warburg et al. (2006) and Seelhorst and Liu (2015) since it uses the same methodological instrument but addresses specifically airline brand equity. In addition, this paper represents the first attempt to attach a monetary value to the brand equity related literature mentioned at the beginning of the literature review.

3. Choice experiment, data, and modeling approach

3.1. Choice experiment

As already indicated in the literature review, stated choice experiments are more interested in the individual valuation of certain attributes and the corresponding (WtP), whereas revealed choice analyses are mainly used in demand forecasting. The reason for such methodological differences is that revealed choices are potentially influenced by latent attributes, which could distort WtP estimates. By contrast, stated choice experiments occur in a well-defined and controlled experimental environment, in which only the attributes of interest are tested, thus leaving no space for distortions out of latent variables and measurement

[4] In addition to reliability and safety of service, which might also contribute to airline image due to past passenger experiences.

problems.[5] Since we are interested in passengers' valuation, we developed a binary stated choice experiment for itinerary choices that reflects typical booking situations of passengers. In the choice experiment, respondents were confronted with two alternatives, Ryanair and another LCC airline for a typical medium-haul itinerary in Europe. The persistence of negative media coverage over time, as mentioned in the introduction, suggests that this airline has a fundamental reputation problem that goes beyond the rest of the LCCs. Consequently, this paper aims to identify the airline (total) brand equity effect, relative to the next possible airline. The experiment considered the following attributes: ticket price, checked baggage, extra legroom, food and beverage, and priority boarding as choice-related attributes. Table 2 shows the attributes and their levels. Therefore, the analysis includes the classical trade-offs between ticket prices and airline service attributes. One of the alternatives is always Ryanair, randomly displayed left or right on the screen. Ticket prices are based on typical fares for a continental European flight to create a realistic scenario. We used a fractional orthogonal design to reduce the 96 choice combinations (Bliemer & Rose, 2010; Louviere et al., 2000, 2010) and blocked them into six repetitions per respondent.

Before looking at the six choice situations, participants were asked to imagine the scenario shown in Table 3.

Table 4 shows one of the possible choice situations. Note that the occurrence of Ryanair in the first or second place was chosen randomly to avoid bias due to the order of airlines.

The survey was administered in the winter 2023–2024. The randomly chosen respondents were contacted on four consecutive Saturdays in different marketplaces around Berlin and were invited to participate in the online survey. With this approach it was ensured that also possible commuters (who are normally not available during the week) were part of the survey. Upon acceptance, respondents were given the survey link, to which they participated later. The survey included the six choice scenarios (generated with orthogonal design and blocked down to six) described above and a subsequent section containing several questions with respect to sociodemographic attributes (age, gender, income etc.) of the respondents. A total of 336 participants contributed to the experiment, generating 2016 observations.

This approach provides some advantages but is also associated with disadvantages. Firstly, the experiment includes typical services that passengers can book for LCCs as ancillary services. It is thus ensured that the adopted approach generates realistic choice scenarios that every potential passenger might have experienced in the past. In particular, the attributes included represent ancillary services that passengers can additionally choose when booking a flight. Secondly, the choice experiment is kept as simple as possible (binary choices, few alternative specific variables). Though this comes at the cost of detail accuracy, it ensures that respondents can cognitively handle the choice situations. Yet basic trade-offs still exist in the analysis. Thus, this experimental set-up might be seen as a response to possible hypothetical bias that could distort WtP measures (Hensher, 2010). Thirdly, keeping the choice experiment as simple as possible reduces the required sample size. In our case applying the rule of the thumb presented by Orme (1998) ,[6] the choice experiment would require 209 respondents. With 336 respondents we are thus far beyond that lower bound. Fourthly, the use of orthogonal design allows to reduce the number of choice sets and thus to keep the sample size low. Finally, as Table 1 demonstrates, similar studies have used a great variety of attributes influencing the passengers' preferences und thus the choice of the airline (e.g. departure and arrival time, frequent flyer programs, direct connection etc.). To this end, and in order to avoid possible omitted variable bias, it was additionally emphasized that only the alternatives presented should be considered, while all other choice criteria are identical and should not be taken into consideration. Thus, this approach utilizes the merits of stated choice analyses in offering respondents the choice attributes of interest, while eliminating omitted variable bias.

On the other hand, in such a choice experiment pre-knowledge of respondents might be an additional source of inaccuracies. Therefore, estimations in the following section include a binary variable called "previous experience with Ryanair" associated with pre-knowledge of passengers with Ryanair, therewith trying to capture potential individual predispositions of passengers. This is also in line with the finding in the literature review, that brand equity is also formed by but goes beyond perceived airline quality. However, it is important to note that a similar predisposition might also exist for Full-Service-Carriers (FSC). Consequently, passengers who predominantly travel with FSC expect that the attributes used in the choice experiment are already included within the ticket price. Apart from the fact, that in the meanwhile many FSCs have also introduced the option "only fly" with additional ancillaries (for short-to medium-haul services), it should be pointed out that the choice experiment is performed in a well-defined environment, giving respondents the framework for their answers, still keeping in mind, that this is a potential source of inaccuracy due to passenger pre-knowledge.

In addition, providing only the name of the one airline (Ryanair) in the choice experiment while leaving the other undefined (other airline) is a kind of a semi-labelled experiment. On the one hand this allows to keep complexity at a low level and analyze the impact of airline reputation compared to the rest of all other LCCs as a whole. However, on the other hand, it could possibly lead to some inaccuracies, since respondents do not associate the alternative "Other" with a certain airline. In other words, it could happen that participants penalize the name "Ryanair" in their choice behavior because it's the only one they receive in the experiment. However, this paper is exactly interested in deriving monetary values for the precise case of Ryanair following the persistent negative media reports in the past. That is, the approach seems to be appropriate to test the long-run brand image reputation effect of Ryanair compared to the rest of the market. Nevertheless, in order to address such potential inaccuracies, the following subsections will also perform some "rough" quality tests for WtP measures.

3.2. Model and data

Based on the standard choice modeling approach (McFadden, 1974; Ben-Akiva & Lerman, 1991; Train, 2009) assuming utility maximization, airline i is preferred over airline j in observation t, if the corresponding (indirect) utility U for alternative i (in our case airline 1) is higher than the one for j (in our case airline 2), or formally: $U_{i,t} \geq U_{j,t} \rightarrow i \succ j$. Note that in the dataset each respondent shows up several times, but we ignore this in the presentation of the model for simplicity. Splitting $U_{i,t}$ into a deterministic (V_{it}) and a stochastic component (ε_{it}), results in: $U_{it} = V_{it} + \varepsilon_{it}$. The deterministic part includes all observable influences on the choices. Assuming independently and Gumbel distributed error

Table 2
Attribute Values of the choice experiment.

Ticket price (TP)	€120 to €170 in six increments of €10
Checked baggage (CB)	No (=0); Yes (=1)
Legroom included (L)	No (=0); Yes (=1)
Food and Beverages included (FB)	No (=0); Yes (=1)
Priority boarding included (PB)	No (=0); Yes (=1)

[5] In particular the set of alternatives and attribute values of non-chosen alternatives (for an in-depth discussion see Hensher, 2010). Of course, stated preference also have several caveats (see Train (2009) for a discussion).

[6] An in-depth discussion is provided by Assele et al. (2023).

Table 3
Choice situation environment.

Imagine you would like to travel within Europe for one week soon (e.g. Berlin to Barcelona or Berlin to Rome). After a short internet research, you found two possible flights with low-cost carriers. On the following pages you can find the differences between those two offers. Which airline would you choose?

Table 4
Typical choice scenario.

	Ryanair	Other
Ticket Price (TP)	€ 120	€150
Checked Baggage included (CB)	No	Yes
Extra Legroom included (L)	Yes	No
Food Beverage included (FB)	No	Yes
Priority Boarding included (PB)	Yes	No
Your Choice		

terms, one may derive the well-known logit-probability in (Eqn 5) (e.g., Koppelman & Bhat, 2006, p. 28):

$$\Pr(i) = \frac{\exp\ (V_i)}{\sum_{j=1}^{J} \exp\ (V_j)} \tag{1}$$

The deterministic component of the utility is usually linearly specified:

$$V_i = ASC_i + \sum_k \beta_k \cdot x_{ki} \tag{2}$$

where ASC_i represents the base utility for alternative i, x_{ki} are the attributes influencing the airline choice and β_k are the parameters to be estimated. Note that the utility usually depends on alternative-specific (e.g., the ticket price) and passenger-specific (e.g. income and individual perceptions) influences. The latter is not formalized above for convenience. Parameters are estimated by maximizing the log-likelihood function (Train, 2009).

Based on the choice experiment described above (see Table 2 for the relevant attributes), the indirect utility function for Ryanair (V_R) and airline 2 (V_O) is specified in a linear fashion:

$$\begin{gathered} V_R = ASC_{R-O} + \beta_{TP} \cdot TP_R + \beta_L \cdot L_R + \beta_{FB} \cdot FB_R + \beta_{PB} \cdot PB_R + \beta_{CB} \cdot CB_R + \beta_{I_{R-O}} \cdot \frac{I_t}{\bar{I}} \\ + \ldots \end{gathered} \tag{3}$$

$$V_O = ASC_O + \beta_{TP} \cdot TP_O + \beta_L \cdot L_O + \beta_{FB} \cdot FB_O + \beta_{PB} \cdot PB_O + \beta_{CB} \cdot CB_O$$

The alternative specific constant for the other airline ASC_O is fixed at zero. Thus, ASC_{R-O} indicates the base utility difference between Ryanair and the second airline. The same applies to all individual-specific influences (e.g., $\beta_{I_{R-O}}$ for income I). Note that the income I is normalized to its mean. For this reason, ASC_{R-O} represents a bonus or malus of Ryanair in the choice probability of passengers that is associated with the brand name of the airline. In case that passengers penalize the name Ryanair we expect a negative and significant impact of the alternative specific constant and (some of) the individual specific influences.

In addition, we extend our model in two dimensions. In a first model extension, apart from the specification in (Eqn 3), we hypothesize that possible choices toward one of the alternatives might be influenced by individual income in a non-linear fashion. Preliminary tests have revealed a logarithmic relationship, so that V_R transforms to:

$$\begin{gathered} V_R = ASC_{R-O} + \beta_{TP} \cdot TP_R + \beta_L \cdot L_R + \beta_{FB} \cdot FB_R + \beta_{PB} \cdot PB_R + \beta_{CB} \cdot CB_R \\ + \beta_{I_{R-O}} \cdot \log\left(\frac{I_t}{\bar{I}}\right) + \ldots \end{gathered} \tag{4}$$

A second model extension accounts for random taste heterogeneity. Thus, a mixed logit model with a random parameter specification (Train, 2009) is estimated. In such a model, the tastes of individuals vary according to an (a priori defined) density function $f(\beta|\omega)$, where ω is the vector of the parameters (e.g., mean and standard deviation) of the density function. In this case, choice probabilities are given as the integrals of standard logit probabilities over a density of parameters (McFadden & Train, 2000; Revelt & Train, 1998):

$$P_i = \int l_i(\beta) f(\beta|\omega)\ d\beta \tag{5}$$

P_i describes the probability of an individual choosing the alternative i and l_i is the logit probability from (Eqn 1). Parameter estimates are obtained via simulation (maximum simulated likelihood approach; Train, 2009).

The mixed logit model is superior because it addresses several limitations of the standard logit (Train, 2009). Accounting for random taste heterogeneity is of particular importance because it can lead to less biased estimates. On the other hand, mixed logit models are associated with certain difficulties, mainly connected to the choice of the mixing distribution and the number of draws in the simulation. These difficulties might become even more relevant when researchers compute the WtP based on the model results (Daly et al., 2012; Hess et al., 2007). This point will be revisited in the next section.

4. Results and discussion

4.1. Model results

Before proceeding with the model results, Table 5 demonstrates the main descriptive statistics of the experiment.

Table 5 shows at first that household and income distributions of respondents show a typical (and expected) right-skewed distribution. However, in particular for income it seems that low-income categories are overrepresented in the sample, since the sample mean income is with € 1833.4 around € 250 lower than the average net equivalent income in the population (see Destatis, 2024). As the paper demonstrates in the next subsection, the computed disutility effect will depend on the

Table 5
Descriptive statistics.

Flying frequency per year (in % of respondents)					
1 flight	2–5 flights	6–9 flights	10–12 flights	13 or more flights	
36.7 %	40.0 %	11.1 %	5.6 %	6.3 %	
Age distribution (in % of respondents)					
<20	20–29	30–39	40–49	50–59	60 or more
3.9 %	27.6 %	34.5 %	25.7 %	6.9 %	1.4 %
Income distribution in € (in % of respondents)					
<1500	1501–2500	2501–3500	3501–4500	>4501	no response
41.4 %	29.6 %	15.8 %	5.5 %	2.6 %	5.1 %
Household composition (in % of respondents)					
Single-person	2-person	3-person	4-person	5-person or more	
27.6 %	26.0 %	16.6 %	23.2 %	5.5 %	
Gender (in % of respondents)					
Female	Male			No response	
52.1 %	44.9 %			3.0 %	
Past experience with Ryanair	24.3 %				
Airline choice	Ryanair 43.7 %			Other LCC 56.3 %	

passenger's income. For this reason, estimates in this paper should be interpreted as lower bound estimates. Similarly, the average age in the sample of 36.6 years is around 8 years lower than the one in the population (see Destatis, 2023). It is clear that in the sample the 30–39 years group is overrepresented, and the oldest age group is underrepresented. However, the age distribution in the sample seems to fit very well with the age distribution of passengers in Germany according to German Airport Association (see ADV, 2023). The gender distribution seems to reflect very well the population. Around 10 % of the respondents fly more than 10 times per year. Summing up on the sample structure, the sample seems to reflect basic properties of the population, but respondents seem to have a slightly lower income than the German population. Keeping this in mind, this topic will be revisited in the concluding remarks.

Estimations were carried out by use of Biogeme (Bierlaire, 2003). In addition to the alternative-specific attributes, the estimation results include passengers' income, previous experience traveling with Ryanair, and categorization as frequent flyers (binary). Mixed logit models have proven to perform best with triangular distributions and 50,000 (inter-individual) Halton draws, which seems to be sufficiently high for the simulation. The cost coefficient shows no significant standard deviation in any preliminary model. To minimize computing time, the ticket price coefficient is estimated without random taste heterogeneity. This modeling approach also offers advantages for the subsequent WtP measure computation. First, using a triangular distribution may counter possible distorted WtP estimates, which might occur due to the long tails of other mixing distributions (Sillano & Ortuzar, 2005). Second, fixing the cost coefficient avoids the problem of distorted WtP estimates and reduces possible instabilities of the ML model (Revelt & Train, 1998; Sillano & Ortuzar, 2005). Furthermore, the computation of WtP measures is more straightforward since the numerator (coefficient of the attribute in question) varies according to the triangular distribution, and the denominator (the cost coefficient) is a non-random parameter. Consequently, the WtP follows the same distribution as the numerator, and its mean and standard deviation can be derived easily.

Table 6 shows the estimation results according to (Eqn 3) and (Eqn 4). The linear Logit model (LLM) and non-linear Logit model (NLM) differ in how they treat income. While income enters the model in LLM linearly, NLM includes the log of the income.

Additionally, non-nesting hypothesis tests (Horowitz, 1983) reveal that LLM and NLM are equivalent models, whereas ML is superior to both others. This is hardly surprising since mixed logit approaches take into account variation of individual tastes for choices. On the other hand, income does not appear to be significant anymore in the mixed logit approach and has been omitted from the finally presented model. This means that any minor tendency of high-income passengers and frequent flyers to choose the other airline is in ML fully captured by the alternative specific constant.

In general, parameter estimates show the expected signs. The magnitude of most parameters exhibits minimal variation across the models. We consider this as an indicator of robust results. Passengers positively perceive the inclusion of Food and Beverage, Priority Boarding, and extra Legroom in the offer, resulting in a higher probability of choice. As expected, the choice probability decreases with higher prices.

With regards to the paper's scope, it is first observed that the alternative specific constant of the Ryanair alternative for ML (where the disutility effect is solely in the ASC) and for NLM (where the disutility effect is in the ASC and the income) are negative. This suggests that passengers penalize the brand name "Ryanair". In addition, NLM shows that in particular passengers with higher incomes[7] tend to avoid Ryanair. These results can be interpreted as a first indicator of possible financial losses due to airline image issues. Nevertheless, as will be demonstrated below, Ryanair still enjoys a bonus by some of the passengers.

[7] Note that income enters the computations measured as the individual net monthly income.

4.2. Discussion and further computations

In the following we compute WtP values for the flight attributes included in the choice experiment to test whether our models provide reliable and realistic results. The WtP is the substitution rate between travel cost (here ticket price) and the relevant attribute (say X). Since the characteristics under consideration and travel cost enter linearly the utility function, the WtP can be expressed as the ratio of coefficients[8]:

$$WtP = \frac{\partial U/\partial X}{\partial U/\partial TP} = \frac{\partial V/\partial X}{\partial V/\partial TP} = \frac{\beta_X}{\beta_{TP}} \tag{6}$$

NLM and ML show similar WtP values. For the ML, WtP values are triangularly distributed, whereas the standard deviation of the attribute parameter is scaled with the cost coefficient. For the scope of model comparability and plausibility and testing possible inaccuracies, Tables 7 and 8 present the WtP values for NLM and ML.

Table 7 shows the results from NLM including 95 % confidence intervals according to the asymptotic t-test (Armstrong et al., 2001):

$$V = \left(WTP\frac{t_1}{t_2}\right)\left(\frac{t_1 t_2 \rho t^2}{t_2^2 - t^2}\right) \pm \left(WTP\frac{t_1}{t_2}\right)\frac{\sqrt{\left(\rho t^2 - t_1 t_2\right)^2 - (t_1^2 - t^2)(t_2^2 - t^2)}}{(t_2^2 - t^2)} \tag{7}$$

where t_1 and t_1 are the t-ratios of the corresponding estimated coefficients, t is the critical value for the given degree of confidence and ρ is the coefficient of correlation of the parameter estimates. Under the condition that the value in the radical is positive, upper and lower

Table 6
Estimation results.

Variable	LLM	NLM	ML
ASC			
Ryanair	−0.0107	−0.483***	−0.534***
Sigma (Ryanair)			3.87***
Airline 2	Fixed	Fixed	Fixed
Alternative-specific attributes			
Ticket price	−0.0414***	−0.0414***	−0.0631***
Checked baggage	0.786***	0.782***	1.32***
Sigma (Checked Baggage)			3.10***
Food and Beverage	0.479***	0.478***	0.799***
Sigma (Food and Beverage)			2.34***
Legroom	0.565***	0.567***	0.912***
Sigma (Legroom)			1.81***
Priority boarding	0.266***	0.264***	0.393***
Sigma (Priority Boarding)			0.882
Individual-specific attributes			
Income	−0.000243***		
Log(Income)		−0.380***	
Frequent flyer	−0.255	−0.297*	
Previous Experience with Ryanair	0.116	0.146	
Observations	2016	2016	2016
Final LL	−1007.9	−1008.34	−956.8
McFadden adj. R-square	0.232	0.232	0.256

*** 1% significance level.
** 5% significance level.
* 10% significance level.

[8] In other words, we follow the standard economic approach for WtP computation, which is the marginal rate of substitution between the ticket price and the attribute in question. Equation (6) gives in this respect the amount of money the respondents are willing to pay in form of higher ticket prices in order have the attribute in question included.

Table 7
Expected WtP values from NLM with upper and lower bounds.

	Checked Baggage	Extra Legroom	Food and Beverage	Priority Boarding
WtP in €	18.89	13.70	11.55	6.38
Upper bound	23.02	17.65	15.44	10.19
Lower bound	15.04	9.93	7.84	2.66

Table 8
Expected WtP values from ML with standard deviations.

	Checked Baggage	Extra Legroom	Food and Beverage	Priority Boarding
WtP in €	20.92	14.45	12.66	6.23
Standard Deviation	49.13	28.68	37.08	13.98

bounds of WtP will remain positive, even if parameter estimates are negatively correlated.

Similarly, Table 8 presents the corresponding WtP values including the standard deviation. A comparison of Table 7 with Table 8 reveals that expected WtP values are for both models very close to each other. This suggests that both models yield similar results in this respect. Furthermore, Table 9 illustrates airline surcharges for the attributes used in this paper. One may conclude that certainly airlines differentiate such surcharges (according to stage length, destination, time period, etc.). Assuming fully informed airlines, that capture as much as possible the passengers' WtP for those ancillaries, it is obvious that estimated WtP values from both models are close to surcharges set by airlines for these attributes. In this respect price ranges in Table 9 would even justify the high standard deviations derived from these models. It can thus be concluded that possible hypothetical bias (as discussed above) does not seem to substantially distort our estimates. In other words, model results based in hypothetical choices derive WtP measures close to airline surcharges for the attribute in question. This might be seen as a first tentative model validation with real world data. However, it is obvious that ML derives a much higher variability of WtP estimates. In fact, standard deviations seem to be extremely high. This underlines the importance of mixed logit approaches. Since some passengers in the sample will attach a high value to the tested attributes, their WtP will be expectedly very high, whereas for some others the attribute in question will play a minor role. Note that triangular distributions are not necessarily symmetrical. This could result in the typical situation that average passengers have a (slightly) lower WtP than ML indicates (as indicated by NLM in Table 7) and the remaining share of passengers attach a very high value to the attribute in question, thus causing a high standard deviation. On the other hand, the computed high standard deviations might not only be a result of sample heterogeneity, but also due to the nature of stated choice experiments, or even sampling issues. For this reason, the result of high standard deviations is kept as a potential limitation.

In the following, we compute the monetary value of the Ryanair disutility effect. In other words, we determine the amount of money that makes an individual indifferent between identical flights of Ryanair and another low-cost airline. Note that the ML reflects the Ryanair disutility effect solely in the ASC, while the NLM also accounts for the impact of

Table 9
Airline surcharges for additional services. Source: Airlines' website.

Surcharges in €	Checked Baggage	Extra Legroom	Food and Beverage	Priority Boarding
Ryanair	18.99–59.99	11.00–33.00	10.00	6.00–36.00
Easyjet	11.99–48.00	10.49–16.99	9.50	8.25–13.50

individual-specific influences, such as income (in addition to the ASC).

For the ML, the WtP is triangularly distributed since β_{TP} is not a random parameter. Plugging the parameter estimates in (Eqn 6) results in a mean WtP of € 8.46 with a standard deviation of € 61.33. This is the amount people want to pay less on average just because Ryanair offers the flight. On the other hand, the standard deviation reveals that Ryanair still enjoys a bonus by a considerable share of the passengers.

In the following we proceed with a similar computation using the NLM. However, in this model, it is also necessary to consider the impact of income. Table 6 demonstrates that the alternative specific constant as well as the income and frequent flyers contribute to the disutility effect. In the following the frequent flyer effect will be disregarded. Note that (all other things being equal) in order to attract frequent flyers, ticket prices should be € $\frac{-0.297}{-0.0414} = 7.18$ lower than the ones of non-frequent flyers. We thus consider our results to be rather conservative estimates. On the other hand, with increasing income, passengers seem to move toward the alternative airline. Since in NLM income enters the estimations in a logarithmic fashion (as seen in (Eqn 4)), the income effect is positive but with a decreasing rate, thus indicating a diminishing marginal propensity toward the alternative airline. This result is depicted in Fig. 5. The figure illustrates the only-income based monetary disutility for different income categories in the range of € 500 to € 6400 in increments of € 100. In other words, we compute the income-based monetary difference for two identical flights, which makes the passenger indifferent between Ryanair and an alternative airline. The monetary difference varies between € −4.46 (for low-income passengers) and € 5.70 (for high-income passengers). This result corroborates (at least partially) also the findings from the ML model, showing that up to a level of around € 1500 net monthly income, Ryanair still enjoys a bonus by passengers.

However, the disutility effect presented in Fig. 5 results only from income variation. Adding to this the base monetary difference from the ASC $\left(\frac{-0.483}{-0.0414} = 11.67\right)$ (and disregarding frequent flyers), we obtain the full disutility effect for different income levels. This result is depicted in Fig. 6.

Fig. 6 illustrates that the per passenger monetary disutility due to the loss of reputation is positive even at low-income levels. For low-income categories, e.g. € 1,000, the disutility effect sums up to € 9.97. Plugging in this computation to the average income in the sample of € 1833.4, the disutility effect sums up to € 12.38.

To sum up: Both models NLM and ML derive similar results, as indicated by the WtP values and the average disutility effect. Nevertheless, the superiority of ML in this respect is also clearly observable. Whereas NLM derives an average disutility effect of € 12.38, the

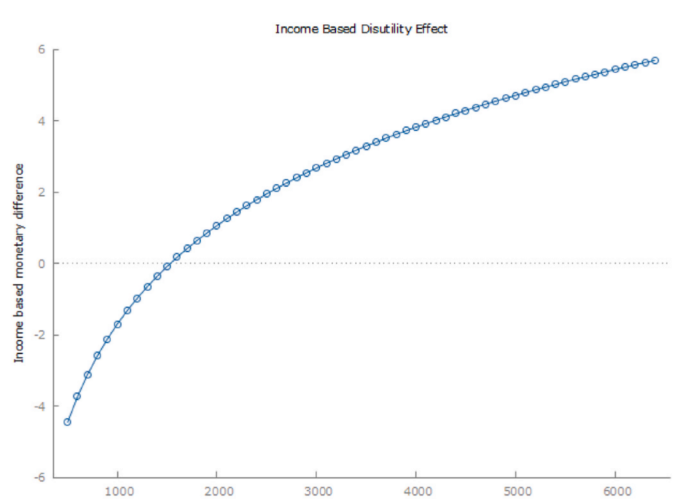

Fig. 5. Disutility effect and income.

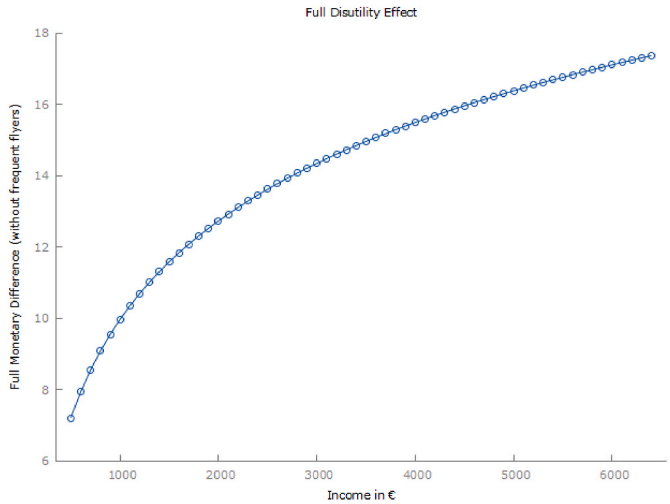

Fig. 6. Full disutility effect for a single passenger.

corresponding figure from ML is slightly lower with € 8.46. However, allowing for heterogeneity of tastes reveals not only much stronger variation in WtP values, but also a Ryanair bonus by some share of passengers. This result is only indicated by NLM (passengers with higher income tend more to the alternative airline) but cannot be fully reached, apparently because income is not the only source of variation of choices with respect to brand name reputation issues. It is also noteworthy that "previous experience with Ryanair" is in all models not significant. Notwithstanding the lacking significance, the parameter estimate is positive in LLM and NLM. This could be interpreted as a bonus for Ryanair by those passengers who have already past experiences with the airline but is a negligible reason for the average passenger in the sample. Exactly this effect is revealed in the ML approach.

These results seem also to confirm the figures presented in the introduction of this paper. As illustrated in Fig. 1 the difference in yields between Ryanair and the group of the other LCCs ranges between € 24.00 and € 39.00. The disutility effect computed above is undoubtedly but one component of this difference since as already discussed many other factors might contribute to it.

After determining the monetary compensation for a single passenger, the potential of an airline to increase its revenues on a typical flight by enhancing its image is examined. Since, however, the distribution of passengers according to their income on a typical Ryanair flight is unknown, it is not possible to provide an estimate for this. Consequently, we undertake sensitivity analyses based on our findings. The typical flight involves the assumption of a standard medium-haul aircraft with 186 seats and a 90 percent load factor. Furthermore, passengers are segmented in six different income categories (in increments of € 1000), and subsequently we vary the distribution of passengers in these categories. Starting with 100 percent of passengers within the lowest income category, this share is then reduced successively down to 40 percent. This approach facilitates the computation of the disutility effect for varying shares of passengers in the lowest income category. Fig. 7 shows these results.

As demonstrated in Fig. 5, the disutility effect for a standard flight ranges from € 1601 to € 2160 and increases with a decreasing share of low-income passengers. However, it must be noted that the accuracy of these figures might be compromised by the assumptions on the income distribution. Therefore, we consider our results as rough estimates.

Notwithstanding this possible distortion, financial gains from enhancing the airline's reputation can be substantial. Even with 100 percent low-income passengers (no expected distortion from income distribution), the disutility effect amounts to approximately € 1601 per flight. Since firm strategies aiming at a better image are costly, economically acting airlines would juxtapose the ability to charge

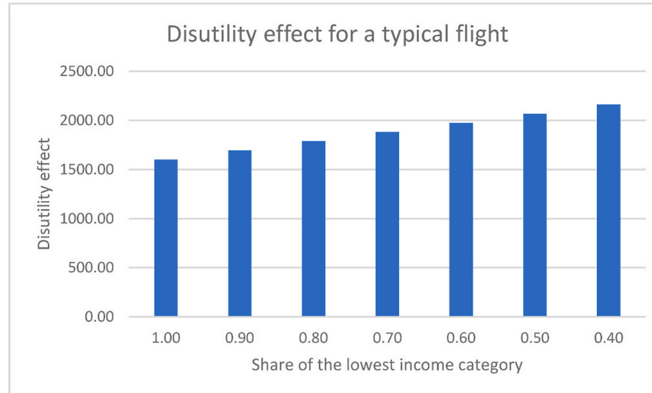

Fig. 7. Lost income [€] for a typical flight. Source: own computations.

higher ticket prices due to a higher reputation with its cost. Assuming even the lowest possible income of € 500 and multiplying the corresponding average disutility effect with the number of passengers transported by Ryanair in 2022 (97.5 million passengers, see Statista, 2023), yields a potential revenue increase of roughly € 702 million. Calculations based on the ML-Modell provide an even higher figure of € 825 million. Note that this figure represents a lower bound, since it assumes the possible lowest passenger income and leaves aside frequent flyers.

These results are in line with the literature discussed in Section 2, particularly with studies emphasizing the significance of brand equity on repurchase intentions (Koech et al., 2023; Prentice et al., 2019; Yang et al., 2012; Chen & Tseng, 2010; Chen & Chang, 2008; Chand et al. 2024). This paper adds to this literature in monetizing this effect. Note that the parameter estimate for "previous experience with Ryanair" is not significant, thus indicating neither a positive nor a negative impact of past Ryanair experience on airline brand choice. This might also be interpreted as an indicator that prior Ryanair experience is fully captured by the alternative specific constant. In this case past experiences with the airline form expected perceived quality in a negative fashion, so that passengers penalize the brand name, but have no expectations from past experiences. This would also be in line with the approach by Jeeradist et al. (2016) but also with those addressing airline loyalty (Koech et al., 2023; Vuong et al., 2024).

The relevant question now is whether these results could hold for all regional markets. As previously discussed, the magnitude of the disutility effect will depend on the passengers' income, thereby raising concerns regarding its transferability to other markets. From this perspective, we propose similar case studies also for other European regional markets. However, it is important to note that given the overrepresentation of low-income passenger groups in the sample these results could still hold for several other European countries with lower average income. The sensitivity analysis presented in this paper (in particular Fig. 7) addresses this issue, leading to the conclusion that an airline can increase its revenues even with a 100 percent share of low-income passengers on board if it enhances its own reputation.

In addition, the results of this paper will certainly not hold for routes operated by a single airline. Enjoying monopolistic power will enable airlines to neglect any brand name related issues in their pricing, as passengers will have no other option but to fly with the only existing carrier. However, as several studies point out, recent LCC network and schedule developments resulted in progressively overlapping LCC networks (Efthymiou & Christidis, 2023; Zhang et al., 2023) with an increasing degree of competition among LCCs (even leading to saturated local markets). Thus, as competition intensifies, the brand name effect will become more relevant in airline pricing. As a result, from the perspective of network development, it is not expected that single LCCs will hold a monopoly position in a considerable share of their network.

Thus, we do not expect a considerable distortion from monopoly routes in the estimates presented above. Certainly, other scheduling related factors, like departure and arrival times or flight frequency will still enable LCCs to charge a premium and ignore brand name related factors, but this will predominantly be relevant for time inelastic business and high-income passengers, who, in any case, are less targeted by LCCs.

5. Final remarks

5.1. Conclusions

This paper addresses the question of how an airline's low reputation enters passenger booking decisions and derives monetary values for such a reputation. Using a binary experiment for airline choices, where one of the alternatives is always Ryanair, and subsequently estimating several logit models (including mixed logit), it is demonstrated that airline reputation enters consumer decisions, at first in form of the alternative specific constant as an average propensity to eschew Ryanair. Furthermore, higher income passengers and frequent flyers show a similar behavior. This finding translates into a premium an average passenger is willing to pay to avoid the airline with the poor reputation respectively a premium an airline can charge if it improves its image. It is demonstrated that this disutility effect increases with increasing passenger income albeit at a decreasing rate. Depending on the modeling approach, an average monetized disutility effect between € 8.46 and € 12.38 was identified. Under certain assumptions, this sums up to a revenue loss of around € 1601 per flight. The brand name effect has been used in in the past in theoretical analyses for schedule competition (e.g. Brueckner & Flores-Fillol, 2007) or for airline alliances (e.g., Brueckner & Whalen, 2000) and has been identified in empirical literature on brand equity, however, without the merits of monetization coming out of discrete choice analysis. This paper provides thus some first estimates of the brand name effect's magnitude, thereby enabling an airline to increase its ticket prices.

Therefore, an airline could generate substantial additional revenue by enhancing its reputation. Whether an airline utilizes this information may also depend on the airline's ability to exploit the potential revenue due to proper revenue management. Nevertheless, the findings of this study suggest that the financial benefits are substantial enough to outweigh the costs associated with enhancing reputation. However, this monetary advantage may only be manifested in the long run. At the beginning of the strategy adoption process aiming at enhancing reputation, the cost will be higher than the ability to increase ticket prices, given the protracted nature of image enhancement. Initially, consumers may exhibit skepticism, but subsequent trust in the airline's intentions is likely to alter their choice behavior. However, this is certainly also a question of how credibly airlines commit themselves to passengers regarding their future intentions.

In fact, possessing a high reputation does not necessarily ensure profitability (Thomas, 2015), as technological efficiency, market structures and market development might strongly influence profitability. Even less efficient and low-reputation airlines might be profitable in a growing market. However, as competition intensifies and/or market volumes decline, the airline image will become increasingly pivotal for financial success.

5.2. Limitations and further research

We have tested reputation effects using Ryanair as an example. Note that the observed effect might be of a different magnitude if one considers other airlines or other regions. Furthermore, since this paper used a typical medium-haul flight, the observed effect might result in different values or even vanish, for a different stage length, particularly for very short distances. Therefore, this paper does not claim generality, however, it can demonstrate substantial revenue losses from a poor reputation for that specific case study. In addition, possible additional limitations consider the nature of the stated choice experiment with hypothetical choices, particularly the possible predisposition of some passengers flying predominantly with FSC.

Since this paper has attached the airline's perceived image to its name, it does not consider the attributes that might contribute to reputation. This is an open question for future research. Finally, it should be noted that the airline's image is expected to play a pivotal role in its overall success in European markets in the future, as according to unofficial statements by industry representatives, significant market exits might take place in the future.

Furthermore, strategic business model decisions might influence airline scheduling. In this respect several studies have shed light on the dynamics of the evolution of the low-cost business model and show, that LCCs adopted in the past also FSC elements (Klophaus et al., 2012), particularly in introducing connecting flights (Maertens et al., 2016). Such indirect connections might alter the dynamics of competition between LCCs and FSCs, as well as within the LCC business model (Morlotti et al., 2020). A passenger utility-based planning approach for the introduction of connecting flights would therefore have the potential to substantially increase airline revenues and contribute to efficiency gains (Birolini et al., 2022). The interplay between the brand image effect addressed in this paper and long-run scheduling issues remains unclear at this point. On the one hand, introducing connecting flights might increase airline image and thus allow for even higher financial gains. On the other hand, introducing low-cost connecting flights might increase the risk of additional financial losses due to intensified competition but also in cases of failed services (where passengers miss the connecting flight) or even confirm the possible negative airline image to passengers in the case of very high connecting times.

Consequently, we advocate for the intensification of research on the factors contributing to airline image and its monetary consequences. This can be done in several additional analyses and with different approaches. Firstly, choice analytic instruments might be applied for longer periods of time in the form of panel data to identify potential alterations in passengers' choice behavior as a response to changing airline image. Secondly, identifying latent (psychological) factors that contribute to airline image could assist airlines in more precise targeting of their marketing and communication activities.

CRediT authorship contribution statement

Christos Evangelinos: Writing – original draft, Visualization, Supervision, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Stefan Tscharaktschiew:** Writing – original draft, Data curation, Conceptualization. **Andy Obermeyer:** Writing – original draft, Validation, Investigation, Data curation, Conceptualization.

Declaration of competing interest

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

The author is an Editorial Board Member for *ReTrEc* and was not involved in the editorial review or the decision to publish this article.

Data availability

Data will be made available on request.

References

ADV. (2023). Umfassende repräsentative Fluggastbefragung: Klarer Trend – Der Passagier wird jünger und Kurzreisen nehmen ab. *ADV-PRESSEMITTEILUNG Nr. 10/2023. Retrieved from.* https://www.adv.aero/umfassende-repraesentative-fluggastbefragung-klarer-trend-der-passagier-wird-juenger-und-kurzreisen-nehmen-ab/. (Accessed 19 April 2014).

Ailawadi, K. L., Lehman, D. R., & Neslin, S. A. (2003). Revenue premium as an outcome measure of brand equity. *Journal of Marketing, 67*, 1–17. https://doi.org/10.1509/jmkg.67.4.1.18688

Akamavi, R. K., Mohamed, E., Pellmann, K., & Xu, Y. (2015). Key determinants of passenger loyalty in the low-cost airline business. *Tourism Management, 46*, 528–545. https://doi.org/10.1016/j.tourman.2014.07.010

Alderighi, M., Cento, A., & Piga, C. A. (2011). A case study of pricing strategies in European airline markets: The London e Amsterdam route. *Journal of Air Transport Management, 17*, 369–373. https://doi.org/10.1016/j.jairtraman.2011.02.009

Allen, J., Bellizzi, M. G., Eboli, L., Forciniti, C., & Mazzulla, G. (2020). Service quality in a mid-sized air terminal: A SEM-MIMIC ordinal probit accounting for travel, sociodemographic, and user-type heterogeneity. *Journal of Air Transport Management, 84*, Article 101780. https://doi.org/10.1016/j.jairtraman.2020.101780

APEX. (2024). Airline fares, profit, schedules, and CO_2 data. https://rdcaviation.com.

Armstrong, P., Garrido, R., & Ortúzar, J.dD. (2001). Confidence intervals to bound the value of time. *Transportation Research Part E, 37*(2–3), 143–161. https://doi.org/10.1016/S1366-5545(00)00019-3

Assele, Y. A., Meulders, M., & Vandebroek, M. (2023). Sample size selection for discrete choice experiments using design features. *Journal of Choice Modelling, 49*, Article 100436. https://doi.org/10.1016/j.jocm.2023.100436

Balcombe, K., Fraser, I., & Harris, L. (2009). Consumer willingness to pay for in-flight service and comfort levels: A choice experiment. *Journal of Air Transport Management, 15*, 221–226. https://doi.org/10.1016/j.jairtraman.2008.12.005

BBC. (2019). *Ryanair named 'worst short-haul airline'*, 5. January 2019 https://www.bbc.com/news/business-46761330. (Accessed 20 June 2023).

Bellizzi, M. G., Eboli, L., & Mazzulla, G. (2020). An online survey for the quality assessment of airlines' services. *Research in Transportation Business & Management, 37*, Article 100515. https://doi.org/10.1016/j.rtbm.2020.100515

Ben-Akiva, M. E., & Lerman, S. R. (1991). *Discrete choice analysis/theory and application to travel demand* (4 ed.). MIT Press.

Bierlaire, M. (2003). Biogeme: A free package for the estimation of discrete choice models. *Ascona, Switzerland: Proceedings of the 3rd Swiss transportation research conference*.

Birolini, S., Besana, E., Cattaneo, M., Redondi, R., & SallanJ, M. (2022). An integrated connection planning and passenger allocation model for low-cost carriers. *Journal of Air Transport Management, 99*, Article 102160. https://doi.org/10.1016/j.jairtraman.2021.102160

Bliemer, M. C. J., & Rose, J. M. (2010). Construction of experimental designs for mixed logit models allowing for correlation across choice observations. *Transportation Research Part B, 44*, 720–734. https://doi.org/10.1016/j.trb.2009.12.004

Bougoure, U. S., Russel-Bennett, R., & Fazal-E-Hasan, S. (2016). The impact of service failure on brand credibility. *Journal of Retailing and Consumer Services, 31*, 62–71. https://doi.org/10.1016/j.jretconser.2016.03.006

Bronnenberg, B. J., Dubé, J.-P., Gentzkow, M., & Shapiro, J. M. (2015). Do pharmacists buy bayer? Informed shoppers and the brand premium. *Quarterly Journal of Economics, 130*(4), 1669–1726. https://doi.org/10.1093/qje/qjv024

Brueckner, J. K., & Flores-Fillol, R. (2007). Airline schedule competition. *Review of Industrial Organization, 30*, 161–177. https://doi.org/10.1007/s11151-007-9140-1

Brueckner, J. K., & Whalen, W. T. (2000). The price effects of international airline alliances. *The Journal of Law and Economics, 43*(2), 503–546. https://doi.org/10.1086/467464

Cantillo, V., Mendieta, O., Cantillo, J., & Cantillo-Garcia, V. (2021). Air travellers' behaviour when choosing airline and flight departure time: The case of medellin, Colombia. *Case Studies on Transport Policy, 9*, 528–537. https://doi.org/10.1016/j.cstp.2021.02.008

Caussade, S., & Hess, S. (2009). An investigation into air travellers willingness to pay for ancillary service attributes within a branded fare context. In *Paper presented at the European transport conference.* October 2009, Leeuwenhorst.

Cavero-Rubio, J. A., & Gonzalez-Morales, M. (2025). Environmental certification and the financial performance of passenger airlines. The mediating effect of image perception, asset management and employee behaviour. *Research in Transportation Business & Management, 58*, Article 101246. https://doi.org/10.1016/j.rtbm.2024.101246

Chang, L.-Y., & Sun, P.-Y. (2012). Stated-choice analysis of willingness to pay for low cost carrier services. *Journal of Air Transport Management, 20*, 15–17. https://doi.org/10.1016/j.jairtraman.2011.09.003

Chen, C.-F., & Chang, Y.-Y. (2008). Airline brand equity, brand preference, and purchase intentions - The moderating effects of switching costs. *Journal of Air Transport Management, 14*, 40–42. https://doi.org/10.1016/j.jairtraman.2007.11.003

Chen, L., Li, Y.-Q., & Liu, C.-H. (2019). How airline service quality determines the quantity of repurchase intention - Mediate and moderate effects of brand quality and perceived value. *Journal of Air Transport Management, 75*, 185–197. https://doi.org/10.1016/j.jairtraman.2018.11.002

Chen, C.-F., & Tseng, W.-S. (2010). Exploring customer-based airline brand equity: Evidence from Taiwan. *Transportation Journal, 49*(1), 24–34.

Chonsolasin, D., Jomnonkwao, S., Chanpariyavatevong, K., Laphrom, W., & Ratanavaraha, V. (2021). Modeling of airline passenger loyalty: A comparison of leisure and business travelers. *Research in Transportation Business & Management.* , Article 100735. https://doi.org/10.1016/j.rtbm.2021.100735

Coldren, G. M., & Koppelman, F. S. (2005). Modeling the competition among air-travel itinerary shares: GEV model development. *Transportation Research Part A, 39*, 345–365. https://doi.org/10.1016/j.tra.2004.12.00

Coldren, G. M., Koppelman, F. S., Kasturinangan, K., & Mukherjee, A. (2003). Modeling aggregate air-travel itinerary shares: Logit model development at a major US airline. *Journal of Air Transport Management, 9*, 361–369. https://doi.org/10.1016/S0969-6997(03)00042-5

Daily Mail. (2017). R. *Yanair bosses 'don't treat crew like humans': Air stewardess reveals how she was forced to sell more snacks to be closer to her ill grandmother as staff tell of their appalling treatment*, 18. December 2017 https://www.dailymail.co.uk/news/article-5192355/Ryanair-bosses-dont-treat-crew-like-humans-say-staff.html. (Accessed 20 June 2023).

Daly, A. J., Hess, S., & Train, K. E. (2012). Assuring finite moments for willingness to pay in random coefficients models. *Transportation, 39*(1), 19–31. https://doi.org/10.1007/s11116-011-9331-3

Destatis. (2023). Bevölkerung Deutschlands im Jahr 2022 um 1,3 % gewachsen. https://www.destatis.de/DE/Presse/Pressemitteilungen/2023/06/PD23_235_12411.html#:~:text=Das%20Durchschnittsalter%20der%20Bev%C3%B6lkerung%20sank,Jahre%20auf%2044%2C6%20Jahre. (Accessed 19 April 2024).

Destatis. (2024). Einkommen und Lebensbedingungen, Armutsgefährdung - Einkommensverteilung (Nettoäquivalenzeinkommen). https://www.destatis.de/DE/Themen/Gesellschaft-Umwelt/Einkommen-Konsum-Lebensbedingungen/Lebensbedingungen-Armutsgefaehrdung/Tabellen/einkommensverteilung-mz-silc.html. (Accessed 19 April 2024).

Dirsehan, T., & Kurtulus, S. (2018). Measuring brand image using a cognitive approach: Representing brands as a network in the Turkish airline industry. *Journal of Air Transport Management, 67*, 85–93. https://doi.org/10.1016/j.jairtraman.2017.11.010

Eboli, L., Bellizzi, M. G., & Mazzulla, G. (2022). A literature review of studies analysing air transport service quality from the passengers' point of view. *Promet - Traffic & Transportation, 34*(2), 253–269. https://doi.org/10.7307/ptt.v34i2.4020

Efthymiou, M., & Christidis, P. (2023). Low-cost carriers route network development. *Annals of Tourism Research, 101*, Article 103608. https://doi.org/10.1016/j.annals.2023.103608

Espino, R., Martin, J. C., & Roman, C. (2008). Analyzing the effect of preference heterogeneity on willingness to pay for improving service quality in an airline choice context. *Transportation Research Part E, 44*, 593–606. https://doi.org/10.1016/j.tre.2007.05.007

Evangelinos, C., Staub, N., Marcucci, E., & Gatta, V. (2021). The impact of airport parking fees on the tourist's airport airline choice behavior. *Journal of Air Transport Management, 90*, Article 101961. https://doi.org/10.1016/j.jairtraman.2020.101961

Farooq, M. S., Salam, M., Fayolle, A., Jaafar, N., & Ayupp, K. (2018). Impact of service quality on customer satisfaction in Malaysia airlines: A PLS-SEM approach. *Journal of Air Transport Management, 67*, 169–180. https://doi.org/10.1016/j.jairtraman.2017.12.008

Fernandez, J. (2024). Ryanair's consideration scores hold steady despite low consumer perception scores. *YouGov*, 12th March 2024 https://business.yougov.com/content/48900-ryanairs-consideration-scores-hold-steady-despite-low-consumer-perception-scores. January, 2025.

Focus. (2019). Ryanair landet in Rumänien statt in Griechenland - und lässt Fluggäste dort zurück, 08. January 2019. https://www.focus.de/reisen/flug/passagiere-gestrandet-ryanair-landet-in-rumaenien-statt-in-griechenland_id_10150324.html. (Accessed 20 June 2023).

Freund-Feinstein, U., & Bekhor, S. (2017). An airline itinerary choice model that includes the option to delay the decision. *Transportation Research Part A, 96*, 64–78. https://doi.org/10.1016/j.tra.2016.12.004

Hameed, I., Chatterjee, R. S., Zainab, B., Tzhe, A. X., & Yee, L. S. (2024). Navigating loyalty and trust in the skies: The mediating role of customer satisfaction and image for sustainable airlines. *Sustainable Futures, 8*, Article 100299. https://doi.org/10.1016/j.sftr.2024.100299

Hensher, D. A. (2010). Hypothetical bias, choice experiments and willingness to pay. *Transportation Research Part B, 44*, 735–752. https://doi.org/10.1016/j.trb.2009.12.012

Hess, S., Adler, T., & Polak, J. W. (2007). Modelling airport and airline choice behaviour with the use of stated preference survey data. *Transportation Research Part E, 43*, 221–233. https://doi.org/10.1016/j.tre.2006.10.002

Hess, S., & Polak, J. W. (2005). Mixed logit modelling of airport choice in multi-airport regions. *Journal of Air Transport Management, 11*, 59–68. https://doi.org/10.1016/j.jairtraman.2004.09.001

Hess, S., & Polak, J. W. (2006). Airport, airline and access mode choice in the San Francisco Bay area. *Papers in Regional Science, 85*(4), 544–567. https://doi.org/10.1111/j.1435-5957.2006.00097.x

Horowitz, J. L. (1983). Statistical comparison of non-nested probabilistic discrete choice models. *Transportation Science, 17*(3), 319–350. https://doi.org/10.1287/trsc.17.3.319

Hussain, R., Al Nasser, A., & Hussain, Y. K. (2015). Service quality and customer satisfaction of a UAE-based airline: An empirical investigation. *Journal of Air Transport Management, 42*, 167–175. https://doi.org/10.1016/j.jairtraman.2014.10.001

Ishii, J., Jun, S., & Van Dender, K. (2009). Air travel choices in multi-Airport markets. *Journal of Urban Economics, 65*, 216–227. https://doi.org/10.1016/j.jue.2008.12.001

Jeeradist, T., Thawesaengskulthai, N., & Sangsuwan, T. (2016). Using TRIZ to enhance passengers' perceptions of an airline's image through service quality and safety. *Journal of Air Transport Management, 53*, 131–139. https://doi.org/10.1016/j.jairtraman.2016.02.011

Klophaus, R., Conrady, R., & Fichert, F. (2012). Low cost carriers going hybrid: Evidence from Europe. *Journal of Air Transport Management, 23*, 54–58. https://doi.org/10.1016/j.jairtraman.2012.01.015

Koech, A. K., Buyle, S., & Macario, R. (2023). Airline brand awareness and perceived quality effect on the attitudes towards frequent-flyer programs and airline brand choice – Moderating effect of frequent-flyer programs. *Journal of Air Transport Management, 107*, Article 102342. https://doi.org/10.1016/j.jairtraman.2022.102342

Koppelman, F. S., & Bhat, C. (2006). A self instructing course in mode choice modelling: Multinomial and nested logit models. *Paper prepared for the U.S. Department of Transportation Federal Transit Administration*.

Liou, J. J. H., & Tzeng, G.-H. (2007). A non-additive model for evaluating airline service quality. *Journal of Air Transport Management, 13*, 131–138. https://doi.org/10.1016/j.jairtraman.2006.12.002

Louviere, J., Hensher, D., Swait, J., & Adamowicz, W. (2000). Design of choice experiments. In J. J. Louviere, D. A. Hensher, & J. D. Swait (Eds.), *Stated choice methods: Analysis and applications* (pp. 111–137). Cambridge University Press. https://doi.org/10.1017/CBO9780511753831.005.

Louviere, J., Pilhens, D., & Carson, R. (2010). Design of discrete choice experiments: A discussion of issues that matter in future applied research. *The Journal of Choice Modelling, 4*(1), 1–8. https://doi.org/10.1016/S1755-5345(13)70016-2

Lurkin, V., Garrow, L. A., Higgins, M. J., Newman, J. P., & Schyns, M. (2017). Accounting for price endogeneity in airline itinerary choice models: An application to Continental U.S. markets. *Transportation Research Part A, 100*, 228–246. https://doi.org/10.1016/j.tra.2017.04.007

Maertens, S., Pabst, H., & Grimme, W. (2016). The scope for low-cost connecting services in Europe — Is self-hubbing only the beginning? *Research in Transportation Business & Management, 21*, 84–93. https://doi.org/10.1016/j.rtbm.2016.08.004

Martin, J. C., Roman, C., & Espino, R. (2011). Evaluating frequent flyer programs from the air passengers' perspective. *Journal of Air Transport Management, 17*, 364–368. https://doi.org/10.1016/j.jairtraman.2011.02.008

McCandless, S. (2024). The best and worst UK-based airlines for customer service revealed. *Euronews*, 2nd August 2024 https://www.euronews.com/business/2024/08/02/the-worst-uk-based-airline-for-customer-service-which-tells-all. January, 2025.

McFadden, D. (1974). Conditional logit analysis of qualitative choice behaviour. In P. Zarembka (Ed.), *Frontiers in econometrics* (pp. 105–142). Academic Press.

McFadden, D., & Train, K. (2000). Mixed MNL models of discrete response. *Journal of Applied Econometrics, 15*(5), 447–470. https://doi.org/10.1002/1099-1255(200009/10)15:5<447::AID-JAE570>3.0.CO;2-1

Milioti, C. P., Karlaftis, M. G., & Akkogiounoglou, E. (2015). Traveler perceptions and airline choice: A multivariate probit approach. *Journal of Air Transport Management, 49*, 46–52. https://doi.org/10.1016/j.jairtraman.2015.08.001

Morlotti, C., Birolini, S., Cattaneo, M., & Redondi, R. (2020). Introducing connecting flights in LCCs' business model: Ryanair's network strategy. *Journal of Air Transport Management, 87*, Article 101849. https://doi.org/10.1016/j.jairtraman.2020.101849

Morlotti, C., Birolini, S., Malighetti, P., & Redondi, R. (2023). A latent class approach to estimate air travelers' propensity toward connecting itineraries. *Research in Transportation Economics, 99*, Article 101283. https://doi.org/10.1016/j.retrec.2023.101283

Orme, B. (1998). Sample size issues for conjoint analysis studies. *Sequim: Sawtooth Software Technical Paper. Research.* Paper Series 98382.

Osaki, T., & Kubota, Y. (2016). Perceptions of premium service and superiority: Why do customers pay more for high-value-added domestic airline services in Japan? *Journal of Air Transport Management, 57*, 196–201. https://doi.org/10.1016/j.jairtraman.2016.08.004

Pabla, H., & Soch, H. (2023). Up in the air! airline passenger's brand experience and its impact on brand satisfaction mediated by brand love. *Journal of Air Transport Management, 107*, Article 102345. https://doi.org/10.1016/j.jairtraman.2022.102345

Parasuraman, A., Zeithami, V. A., & Berry, L. L. (1985). A conceptual model of service quality and its implications for future research. *Journal of Marketing, 49*(4), 41–50. https://doi.org/10.2307/1251430

Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1988). Servqual: A multiple-item scale for measuring consumer perceptions. *Journal of Retailing, 64*(1), 12.

Pels, E., Nijkamp, P., & Rietveld, P. (2003). Access to and competition between airports: A case study for the San Francisco Bay area. *Transportation Research Part A: Policy and Practice, 37*(1), 71–83. https://doi.org/10.1016/S0965-8564(02)00007-1

Pels, E., Nijkamp, P., & Rietveld, P. (2010). Airport choice in a multiple airport region: An empirical analysis for the San Francisco Bay area. *Regional Studies, 35*(1), 1–9. https://doi.org/10.1080/00343400120025637

Pels, E., Njegovan, N., & Behrens, C. (2009). Low-cost airlines and airport competition. *Transportation Research Part E, 45*(2), 335–344. https://doi.org/10.1016/j.tre.2008.09.005

Percin, S. (2018). Evaluating airline service quality using a combined fuzzy decision-making approach. *Journal of Air Transport Management, 68*, 48–60. https://doi.org/10.1016/j.jairtraman.2017.07.004

Prentice, C., Wang, X., & Correia Loureiro, S. M. (2019). The influence of brand experience and service quality on customer engagement. *Journal of Retailing and Consumer Services, 50*, 50–59. https://doi.org/10.1016/j.jretconser.2019.04.020

Proussaloglou, K., & Koppelman, F. S. (1999). The choice of air carrier, fight, and fare class. *Journal of Air Transport Management, 5*, 193–201. https://doi.org/10.1016/S0969-6997(99)00013-7

Revelt, D., & Train, K. (1998). Mixed logit with repeated choices: Households' choices of appliance efficiency level. *The Review of Economics and Statistics, 80*(4), 647–657. https://doi.org/10.1162/003465398557735

Sattler, H., Völckner, F., Riediger, C., & Ringle, C. M. (2010). The impact of brand extension success drivers on brand extension price premiums. *International Journal of Research in Marketing, 27*, 319–328. https://doi.org/10.1016/j.ijresmar.2010.08.005

Seelhorst, M., & Liu, Y. (2015). Latent air travel preferences: Understanding the role of frequent flyer programs on itinerary choice. *Transportation Research Part A, 80*, 49–61. https://doi.org/10.1016/j.tra.2015.07.007

Sengupta, A. S., Balaji, L. S., & Krishnan, B. C. (2015). How customers cope with service failure? A study of brand reputation and customer satisfaction. *Journal of Business Research, 68*, 665–674. https://doi.org/10.1016/j.jbusres.2014.08.005

Shah, F. T., Sayed, Z., Imam, A., & Raza, A. (2020). The impact of airline service quality on passengers' behavioral intentions using passenger satisfaction as a mediator. *Journal of Air Transport Management, 85*, Article 101815. https://doi.org/10.1016/j.jairtraman.2020.101815

Shen, C., & Yahya, Y. (2021). The impact of service quality and price on passengers' loyalty towards low-cost airlines: The southeast Asia perspective. *Journal of Air Transport Management, 91*, Article 101966. https://doi.org/10.1016/j.jairtraman.2020.101966

Sillano, M., & Ortuzar, J.d. D. (2005). Willingness-to-pay estimation with mixed logit models: Some new evidence. *Environment and Planning A, 37*, 525–550. https://doi.org/10.1068/a36137

Statista. (2023). Anzahl der Passagiere der Ryanair Group in den Geschäftsjahren* 2011 bis 2023. https://de.statista.com/statistik/daten/studie/254375/umfrage/passagierzahlen-von-ryanair/. (Accessed 5 December 2023).

The Guardian. (2018). Ryanair strike: Unions accuse airline of breaching labour laws. https://www.theguardian.com/business/2018/aug/09/unions-accuse-ryanair-of-breaching-labour-law-after-crews-go-on-strike. (Accessed 20 June 2023).

The Irish Times. (2019). *Ryanair lands at the bottom of UK airline tables for sixth year*, 05. January 2019 https://www.irishtimes.com/life-and-style/travel/ryanair-lands-at-the-bottom-of-uk-airline-tables-for-sixth-year-1.3747949. (Accessed 20 June 2023).

Thomas, M. (2015). Ryanair: Success before love. *Strategic Direction, 31*(8), 1–3. https://doi.org/10.1108/SD-02-2015-0034

Train, K. E. (2009). *Discrete choice methods with simulation*. Press Syndicate of the University of Cambridge.

Vuong, B. N., Voak, A., Hossain, S. F., Phuoc, N. T., & Dang, L. H. (2024). The impact of corporate social responsibility on customer loyalty through brand trust and brand reputation: Evidence from low-cost airlines. *Transportation Research Procedia, 80*, 111–118. https://doi.org/10.1016/j.trpro.2024.09.015

Warburg, V., Bhat, C., & Adler, T. (2006). Modeling demographic and unobserved heterogeneity in air passengers' sensitivity to service attributes in itinerary choice. *Transportation Research Record, 1951*(1), 7–16. https://doi.org/10.1177/0361198106195100102

Wen, C.-H., & Lai, S.-C. (2010). Latent class models of international air carrier choice. *Transportation Research Part E, 46*, 211–221. https://doi.org/10.1016/j.tre.2009.08.004

Yang, K.-. C., Hsieh, T.-C., Li, H., & Yang, C. (2012). Assessing how service quality, airline image and customer value affect the intentions of passengers regarding low cost carriers. *Journal of Air Transport Management, 20*, 52–53. https://doi.org/10.1016/j.jairtraman.2011.12.007

Zhang, H., Czerny, A. I., Grimme, W., & Niemeier, H.-M. (2023). The big three EU low cost carriers before and during the Covid-19 pandemic: Network overlaps and airfare effects. *Research in Transportation Economics, 97*, Article 101235. https://doi.org/10.1016/j.retrec.2022.101235