AIRLINE CHOICE MODEL FOR AN INTERNATIONAL ROUND-TRIP FLIGHT CONSIDERING OUTBOUND AND RETURN FLIGHT SCHEDULES

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Abstract:

This paper quantified the impact of outbound and return flight schedule preferences on airline choice for international trips. Several studies have used airline choice data to identify preferences and trade-offs of different air carrier service attributes, such as travel time, fare and flight schedule. However, estimation of the effect return flight schedules have on airline choice for an international round-trip flight has not yet been studied in detail. Therefore, this study introduces attributes related to return flight characteristics and round-trip flight schedule interaction into the airline choice models, which have not previously been reported in the literature. We developed a stated preference survey that includes round-trip fares based on flight schedule combinations and the number of days prior to departure fares was purchased. We applied modelling techniques using a set of stated preference data. A mixed logit model was tested for the presence of heterogeneity in passengers' preferences. Our results indicated that models with attributes related to return flight and its interaction with outbound flight attributes have a superior fit compared with models only based on attributes reported in the literature review. The model found shows that airfare, travel time, arrival preference schedule in the outward journey, departure preference in the return journey and the schedule combination of round-trip flight are significantly affecting passenger choice behaviour in international round-trip flights. Sensitivity analysis of airline service characteristics and their marketing implications are conducted. The analysis reports seven policies with the greatest impact on each airline choice probabilities. It shows that by reducing travel time and airfare and by adopting an afternoon and night schedule preference for outbound and return flight, respectively, the highest probability on airline choice would be reached. This research contributes to the current literature by enhancing the understanding of how passengers choose airlines, considering both outbound and inbound journey characteristics. Thus, this study provides an analytical tool designed to provide a better understanding of international round-trip flight demand determinants and support carrier decisions.

Keywords: round-trip , return flight, flight schedule interaction, passenger choice behaviour

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1. Introduction

According to IATA's latest World Air Transport Statistics publication, North America is the main market to which air transport in Latin America is moving (IATA, 2019). This market transported during 2019 to 10,038,856 million passengers, implying a 1.60% growth compared to 2018 (ALTA, 2020). In fact, the Federal Aviation Administration (FAA) has predicted South America to be the fastest-growing region for commercial air transport over the next two decades. Colombia is the third best-connected country in Latin America behind Mexico, and Brazil and its air connectivity have increased by 34% in the last five years (World-Bank, 2019). This represents a substantial growth performance, broadly in line with the world average over the same period. Colombia, with its advantageous geographical location and its potential to act as a regional centre stands out as a very important network of international connections. To which can be added the fact that Medellin is the Latin America centre for the fourth industrial revolution, making it a particularly attractive destination.

International air transportation has undergone substantial changes in the last decade, one of which has been the increased number of airlines offering commercial flights. This growth in numbers of air carriers has led to an increase in competition among them. Thus, airlines must develop effective marketing and operating strategies that can meet travellers' needs. This raises the need to understand what influences passengers to fly with one air carrier versus others. However, the choices air travellers make for international round-trip flights are complex and involve varying decisions related to the two journeys. Balobaba, Odoni and Barnhart (2015) defined the typical air trip as consisting of two steps: an outbound air trip and an inbound air trip. Therefore, passenger choices for a round-trip flight should be based on the outward and return journey characteristics to a better reality understanding. Although many studies have estimated the factors that influence a round-trip flight preferences (Freund-Feinstein and Bekhor, 2017; Lurkin *et al.*, 2017; Yen and Chen, 2017; Gao and Koo, 2014; Mumbower, Garrow and Higgins, 2014; Yang, Lu and Hsu, 2014; Fleischer, Tchetchik and Toledo, 2012; Brey and Walker, 2011; Theis *et al.*, 2006), most have focussed on outbound flight attributes. Thus, to fill the research gap, this study introduces attributes related to return flight characteristics and round-trip flight schedule interaction into the airline choice models, which have not previously been reported in the literature.

This study intends to ascertain what influences the process of deciding which air carrier to fly. To attain this objective, we analyse the most important route connecting the United States and Colombia, which is currently served by four airlines: Avianca, Viva Air, American Airlines and Copa Airlines. All airlines offer non-stop flights except for Copa Airlines, which only has one-stop flights. A stated preference (SP) experiment was conducted to analyse passenger choice behaviour with respect to an international round-trip. The SP experiment considered six attributes: round-trip fare, travel time, flight frequency, arrival schedule preference at the destination and departure schedule preference from the destination on the return flight. The main goal here is to develop airline choice models that enable air carriers to identify traveller preferences on international round-trip flights. Multinomial logit (MNL) and mixed logit (ML) models were used to identify important explanatory variables affecting airline choice. These models measure travellers' trade-offs among round-trip fare levels, travel time, schedule convenience offered by outbound flight and return flight. Sensitivity analysis was calculated from the estimated coefficients of the airline choice models. These estimations provide valuable insights into how best to develop strategies.

This study contributes to the current literature by improving the understanding of how travellers choose airlines, considering both outbound and inbound journey characteristics. Thus, this research provides an analytical tool designed to provide a better understanding of round-trip flight demand determinants and support carrier decisions on operating, pricing, yield management, and marketing strategies.

2. Literature review

Regarding air traveller choice behaviour, outbound trip decisions have received the most attention in the existing literature (Hossain, Saqib and Haq, 2018; Koo, Caponecchia and Williamson, 2018; Yen and Chen, 2017; Lee and Yip, 2017; Drabas and Wu, 2013; Chang and Sun, 2012; Wen and Lai, 2010; Balcombe, Fraser and Harris, 2009). Most of them have proposed that travellers' choice behaviour is influenced by three important factors: attributes of

airlines, traveller socioeconomic characteristics and travel experiences.

Regarding traveler characteristics, Alex, Manju and Isaac (2019) suggested that transportation planners require travel demand models to predict traveller behaviour with different socioeconomic characteristics. Therefore, demographic characteristics are also important for airline choice, although socioeconomics properties vary in each research. For instance, Balcombe, Fraser and Harris (2009) included age, income, gender and education as dummy variables in the choice experiment. Their model shows that socioeconomic factors have an impact on willingness to pay for in-flight service and comfort levels Chang and Sun (2012) and de Luca (2012) and later study by Drabas and Wu (2013) reported that age and income levels affect airline choice in international flights. Rose et al. (2012) found that age and gender, as well as an interaction term among them, play an important role in the airline choice. Milioti, Karlaftis and Akkogiounoglou (2015) had extensive socio-demographic variables including age, gender, income, nationality and education level of the passengers. They found that those factors affect travellers' decisions regarding airline choice.

Numerous studies have been conducted into the trip experience attributes that travellers take into account when choosing an airline. Travel frequency (Lee, Kim and Sim, 2019; Aksoy, Atilgan and Akinci, 2003) and membership in frequent flyer program (FFP) (Wu and So, 2018; Freund-Feinstein and Bekhor, 2017; Seelhorst and Liu, 2015; Wen, Chen and Huang, 2009) attributes are the most identified in the literature. For instance, Aksoy, Atilgan and Akinci (2003) found a significant relationship between travel frequency and travel purpose in five European airlines. In terms of FFPs, passenger loyalty has been associated with membership in FFP. In this regard, Wen, Chen and Huang (2009) calibrated models in which FFPs attribute affects travellers' choice behaviour. They collected information for two international routes and found that passengers who are FFPs members of different carriers have high loyalty. The most recent research conducted by Wu and So (2018) and Seelhorst and Liu (2015) assessed the FFP membership in two different statuses. Their studies revealed that the different statuses contribute positively to the utility of choosing an airline that provides FFP membership.

Many researchers have explored the airline attributes that travellers consider when choosing a carrier. Airfare, travel time and flight schedule attributes have been identified as important attributes for airline choice. Although airline choice for a round-trip flight has been studied, choice has been focused on attributes of outbound flight. Based on literature review, round-trip fare has been the only attribute that considers the interaction between outbound and return flight characteristics. For instance, Yen and Chen (2017) found a positive relationship between round-trip fare, travel time, service attributes and passenger's choice of airline from Taipei to Shanghai. Lurkin *et al.*, 2017; Fleischer, Tchetchik and Toledo, 2012 also support the idea that round-trip fare is associated with travellers choice behaviour. Lurkin *et al.*, 2017; Lurkin *et al.*, 2018 included outbound flight attributes and assessed the departure time of day as an explanatory variable of airline itinerary choice in round-trip flights. Regarding the airline flight schedule, this attribute has been assessed for a single trip. Wen and Lai (2010), Zhang (2012) and Wen, Chen and Fu (2014) examined the relationship between schedule delay and passenger's choice behaviour. They defined schedule delay as the difference between preferred and actual departure time of flight. Their results indicated that air travellers are willing to pay a high amount to have a preferred departure time.

Based on the literature review of air round-trip flights, airline attributes were based only on outbound flight characteristics. To fill up this gap, we integrated attributes related to return flight characteristics and attributes related to the interaction between outbound and return flight variables. Thus, the aim research is to find a model with a better Goodness-of-Fit in comparison to the models that not consider round-trip attributes. In other words, this is the first study to consider the outbound and inbound flight schedules preference in an airline choice.

The above studies indicate the importance of including airline attributes, passenger characteristics and trip experience variables into the airline choice models. Therefore, in this study, we show how a round-trip fare, trip duration, departure and arrival schedule attributes affect the passenger choice behaviour in an international round-trip flight.

3.   Model structure

Several studies have researched traveller choice behaviour, many of which have applied discrete choice models to obtain useful information on how travellers select trip alternatives. Previous air travel choice behaviour studies have been based on random utility theory (Domencich and McFadden, 1975) and various discrete choice models have been developed. MNL models have the simplest structure and are the most used model formulation for travel choice. Nested logit (NL) models are complex and allow correlation between different alternatives. Flexible ML models allow the capture of heterogeneity, which is referred to as differences between consumers. The ML model uses a random parameter specification to explain unobserved heterogeneity across travellers and solves the MNL and NL models' main limitations.

Discrete choice models are often used in the air transportation market to analyse airline marketing problems. This study adopts the random utility theory, which represents the theoretical basis of discrete choice modelling, to assess choice behaviour for four airline alternatives (Avianca, American Airlines, Viva Air and Copa Airlines). The random utility theory is an econometric instrument for empirical estimation of the demand function (Domencich and McFadden, 1975). The discrete choice model measures the attractiveness of each airline based on a utility function consisting of two components: a systematic component observed by the researcher and a random error component that includes unobservable effects. Thus, the utility function of airline i for passenger q can be expressed as:

$$U_{iq} = V_{iq} + \varepsilon_{iq)} \tag{1}$$

Where V_{iq} is equal to the representative or systematic utility and ε_{iq} represents the error component for airline i and passenger q.

The random utility function, V_{iq}, depends on airline i's observable attributes and the socioeconomic characteristics of a passenger q. V_{iq} can be expressed by a linear equation that includes parameter vector k (e.g., airfare, travel time, arrival time, departure time, age, education level and gender)

The random utility function, V_{iq}, depends on airline observable attributes, trip experience variables and the socioeconomic characteristics of a passenger q. V_{iq} can be expressed by a linear equation:

$$V_{iq} = \sum_k \beta_{ik} X_{ikq} + \sum_n \theta_{in} Y_{inq} + \\ \sum_m \alpha_{im} Z_{imq} + \sum_p \lambda_{ip} T_{ipq} + \\ \sum_h \delta_{ih} W_{ihq} \tag{2}$$

Where

β_{ik} are parameters related to outbound flight attributes (X_{ik}) (e.g., travel time, arrival schedule, flight frequency).

θ_{in} are parameters related to return flight attributes (Y_{in}) (e.g., departure schedule, flight frequency).

α_{im} are parameters associated with attributes related to the interaction between outbound and return flight variables (Z_{im}) (e.g., round-trip fare, flight schedules interaction).

λ_{ip} are parameters related to travellers characteristics (T_{ip}) (e.g. age, education level).

δ_{ih} are parameters related to trip experience attributes ($W_{ih)}$) (e.g. membership in FFP, trip purpose).

The assessment of θ_{in} and α_{im} parameters are the contribution of this research that had not been covered by other studies within this field. Coefficient vectors $\beta_{ik}, \theta_{in}, \alpha_{im}, \lambda_{ip}, \delta_{ih}$ can be estimated using maximum likelihood methods.

Given equations (1) and (2), the probability that passenger q chooses alternative i can be expressed as:

$$P_{iq} = P\big(V_{iq} + \varepsilon_{iq} \geq V_{jq} + \varepsilon_{jq} \ \forall j \neq i\big) \\ = P\big(\varepsilon_{jq} \leq \varepsilon_{iq} + \big(V_{iq} - V_{jq}\big) \ \forall j \neq i\big) \tag{3}$$

P_{iq} depends on the distribution on the random vector of error terms.

The MNL model is the simplest random utility model and assumes that errors of the utilities are independent and identically follow Gumbel distributions, with a mean of zero and a scale of one (which implies a variance of $\pi 2/6$) (Domencich and McFadden, 1975). Under those assumptions, the probability that alternative i will be chosen is given by:

$$P_{iq} = \frac{exp(V_{iq})}{\sum_{j=1}^{J} \exp (V_{jq})} \tag{4}$$

The MNL model is the most broadly used discrete choice model in air travel research (Tsai and Chen, 2019; Wu and So, 2018; Lee and Yip, 2017; Wen and Yeh, 2017; Seelhorst and Liu, 2015; Yang, Lu

and Hsu, 2014; Chang and Sun, 2012; Rose *et al.*, 2012; Wen and Lai, 2010; Espino, Martín and Román, 2008; Theis *et al.*, 2006); however, it may produce biased parameter estimations and fails to address individual heterogeneity. Recently, more advanced discrete choice models based on an MNL approach have been developed. One such model is the ML model, which enables consideration of traveller heterogeneity by identifying random parameters (McFadden and Train, 2000) that should be set by specifying a random distribution defined by the mean and standard deviation. Thus, the utility of airline *i* for passenger *q* can be expressed as:

$$U_{iq} = \beta'_q X_{iq} + \varepsilon_{iq} \tag{5}$$

where:

β'_q: random parameters that vary over air passengers
X_{iq}: vector of observed variables of airline i for passenger *q*
ε_{iq}: independent and identically distributed as Gumbel

β'_q varies over passengers in the population with the continuous probability density $f(\beta/\theta)$, where θ characterises density with mean and variance parameters. The unconditional probability of passenger *q* choosing airline *i* can thus be expressed as (Train, 2009):

$$P_{iq} = \int \left(\frac{exp(\beta' X_{iq})}{\sum_{j=1}^{J} exp(\beta' X_{jq})} \right) f(\beta/\theta) d\beta \tag{6}$$

Train (2009) also indicated that ML probability does not have a closed-form and can thus be approximated using simulation methods.

4. Empirical investigation

We examine choice behaviour on the route from Medellin (MDE) to Miami (MIA), which is one of the most important routes connecting Colombia with an international destination. The MDE-MIA-MDE round-trip is currently served by The MDE-MIA-MDE round-trip flight is currently served by three full-service carriers: Avianca (AVA), American Airlines (AAL), and Copa Airlines (CMP) and one low-cost carrier: Viva Air (VVC). We chose this route based on three criteria. First, the Colombia to Miami route has the most passengers carried per year on international flights in the Colombian air market. Second, both cities are served by a low-cost airline. Additionally, the MDE-MIA route is the only non-stop flight route served by VVC. Third, VVC and AAL have the highest numbers of passengers carried between MDE and MIA yearly compared to other journeys from Colombia to MIA. Table 1 shows some passenger flow values. This route is particularly relevant because VVC, AVA, AAL and CMP compete over it by providing passengers with options regarding airfares, travel time, frequencies, departure and arrival schedules and other attributes.

Our interest focuses on analysing the main factors passengers consider when buying a ticket for an MDE-MIA round-trip.

4.1. Airfare behaviour

Many prior airline choice studies have assumed a fixed fare for SP design (Hossain, Saqib and Haq, 2018; Lee and Yip, 2017; Yen and Chen, 2017; Jung and Yoo, 2014; Wen, Chen and Fu, 2014; Drabas and Wu, 2013; Chang and Sun, 2012; Rose *et al.*, 2012). However, airfare can vary dynamically and significantly even on the same flight. SP design with dynamic pricing is challenging as it is highly influenced by how many days prior to the departure date a flight is booked and the flight schedule.

To determinate the weekly airfare value, we collected airfares from each airline serving in the round-trip over a three-month period. Travel dates were based on a constant two-week round-trip. Airfares were reviewed based on different schedule combinations (morning (M), afternoon (A) and night (N)) between MDE-MIA and MIA-MDE. Fig 1 shows an example of different fare combinations for AVA based on arrival afternoon schedule for MDE-MIA flight and departure morning schedule for MIA-MDE flight (M-A). Thus, AVA offers three fares for MDE-MIA flight in the afternoon schedule and just one fare for MIA-MDE flight in the morning schedule. Moreover, fares were based on seven weeks prior to departure day. Thus, we have three possible combinations for the international round-trip flight in the M-A schedule combination.

Fig 2 shows the average ticket price for the MDE-MIA-MDE route using daily average fare combinations for the four air carriers. Fig 2 also indicates that fares are highest a few days before the departure date. VVC only offers arrival schedule to MIA and departure schedule from MIA in the afternoon; this

means afternoon-afternoon (A-A) flight schedule combinations, whereas AVA has all possible (M, A and N) schedule combinations. For AAL, the M-M and M-A, and N-M and N-A schedules have the same fare combinations, respectively and for AAL, fares booked five days prior to departure are the lowest. The A-M and A-A schedules for CMP show that

fares are lowest between 14 and 35 days prior to departure compared to other schedule combinations. This aligns with AVA fare behaviour. Fig 2 highlights that the round-trip has different fares for each airline depending on schedule combinations of MDE-MIA and MIA-MDE trips and also depends on the number of days prior to departure day fares are purchased.
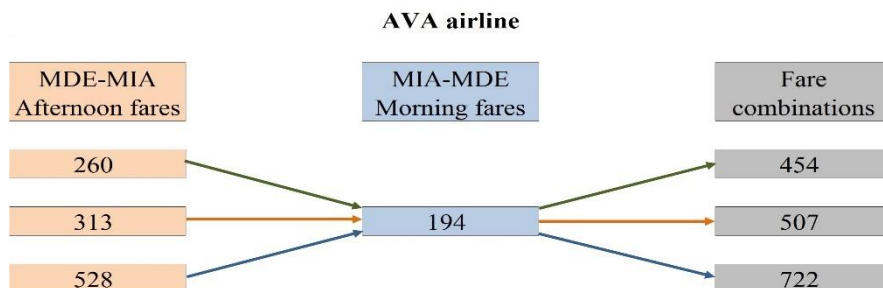

Fig. 1. Fare combinations based on purchase seven weeks prior to departure day (USD)

Table 1. Airline characteristics, Miami destination

Airlines	Departure Airport	Daily frequency		Passengers (year)	Total Passengers(year)
		Non-stop	One-stop		
VVC	MDE	1	--	30,410	
	BOG	--	1	5,739	36,294
	OTHER	--	--	145	
AVA	MDE	1	6	43,084	
	BOG	4	4	102,130	
	CLO	1	5	45,785	282,479
	BAQ	1	4	35,162	
	CTG	1	4	38,359	
	OTHER	--	--	17,959	
AAL	MDE	2	--	74,047	
	BOG	3	7	66,891	
	CLO	1	0	45,999	217,443
	BAQ	1	3	29,471	
	CTG	1	3	1,035	
CMP	BOG	--	6	1,805	
	CTG	--	5	2,946	4,772
	MDE	--	6	*	
	OTHER	--	--	21	
OTHER	MDE	--	--	5,367	
	BOG	--	--	45,813	
	BAQ	--	--	6,655	67,640
	CTG	--	--	1,540	
	OTHER	--	--	8,265	

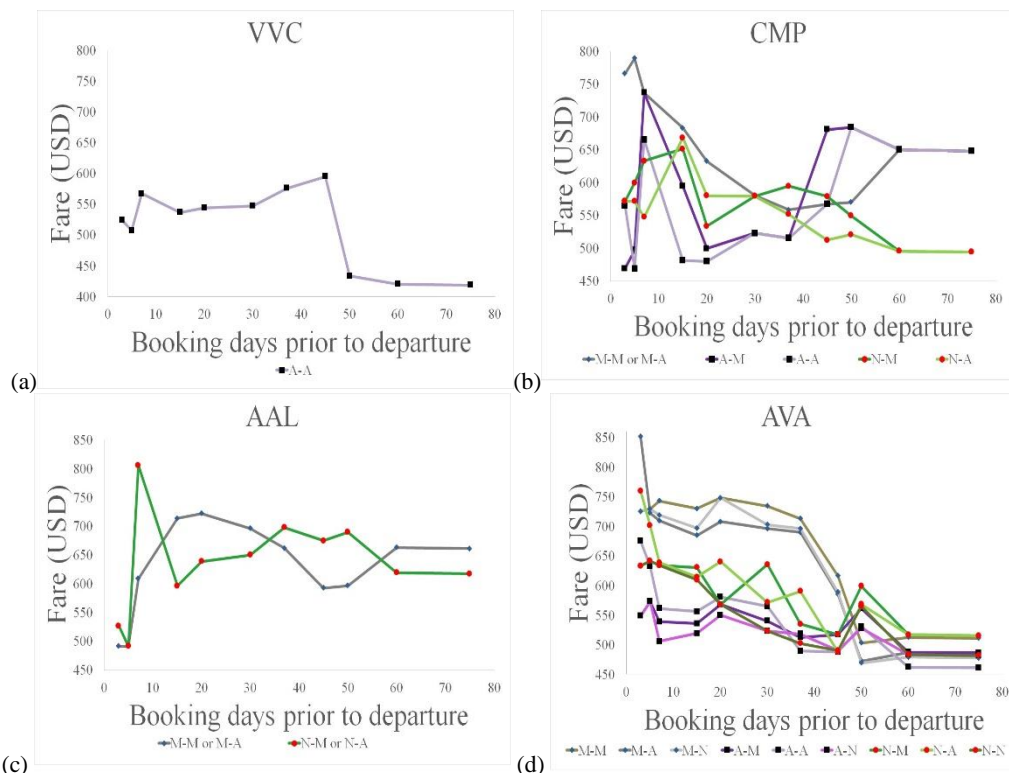Sources: (Aerocivil, 2017)

*Not reported

Fig. 2. Mean fares as a function of days prior to departure day (USD). (a) Viva Air (VVC), (b) Avianca (AVA), (c) American Airlines (AAL) and (d) Copa Airlines (CMP)

4.2. Variables and levels

We identified factors that air travellers consider when deciding which airline to choose using two steps. First, we reviewed previous airline choice behaviour studies to identify pertinent attributes for our research. Second, we conducted qualitative research using focus groups. We selected two focus groups representing frequent fliers, travel agents, academics, airline and airport managers and government officials who helped define airline attributes that could be analysed.

This research conducted an SP experiment to examine traveller preferences. The experiment involved four alternatives. The first airline was VVC, which is a low-cost carrier. The second carrier was AVA, which represents the dominant domestic and international air carrier in Colombia. The third and fourth alternatives were AAL and CMP, respectively, and

they only cover international flights to and from Colombia.

The attributes used in the experiment are round-trip fare (FARE), travel time (TTIME), flight frequencies (FREQ), arrival schedule from MDE to MIA and departure schedule from MIA to MDE. Table 2 shows the set of attributes and levels used in the choice experiment. FARE and FREQ were determined so the values would be like current air carrier operations.

By basing on the days prior to departure day, we calculated mean fares for each airline and for each schedule combination and these were set to be the median level. Seelhorst and Liu (2015), Martín, Martín, Román and Espino (2011); Wen and Lai (2010) and Espino, Martín and Román (2008) reported that the lowest and highest levels can be estimated using mean fares minus 20% and mean fares plus 20%, respectively. Thus, by basing on the fare

combination in Fig 1, we calculated the mean fare as intermediate level, mean fare minus 20% as level 0, and mean fare plus 20% as level 2. The level assignments are consistent with the showed in Fig 1, where level 0 approximately corresponds to the lowest fare combination and level 2 is close to the highest fare combination.

In terms of FREQ, VVC has one non-stop flight per day, AVA has seven per day (one non-stop and six one-stop), AAL has two non-stop flights per day and CMP has six one-stop flights per day. To create three levels at the same increment, we use the current FREQ as the median, with current FREQ plus one and current FREQ minus one as the highest and lowest levels, respectively. TTIME includes in-flight travel time from the origin airport to the destination airport as well as connecting time, which includes waiting in the intermediate airport. Thus, TTIME depends heavily on whether a flight is non-stop or one-stop. TTIME was set at 3.5 hours for non-stop flights and 6 hours and 8.5 hours for one-stop flights. Arrival schedule time difference (ARR) is interpreted as the difference between preferred arrival time and that chosen by SP survey respondents. Departure schedule time difference (DEP) is also a measure of the deviation from a traveller's preferred time of travel. Arrival time at MIA airport and departure time from MIA airport are determined by three levels. Thus, the morning schedule allowance was set to 6 a.m., 9 a.m. and 12 noon; the afternoon schedule allowance was set to 1 p.m., 4 p.m. and 7 p.m.; and the night schedule allowance was set to 8 p.m., 11 p.m. and 2 a.m.

4.3. Stated preference design

A transportation model requires collecting a wide variety of information, derived from different sources, like surveys (Żochowska *et al.*, 2017). SP or stated choice (SC) analysis is an approach widely applied by researchers to understand traveller choice behaviours. The SP survey is based on constructed hypothetical profiles designed to assess preferences for specific attributes. Given the selection of attributes and their associated levels, an SC experiment was conducted using the L^{MA} approach (Hensher, Rose and Greene, 2005). This approach has been widely used in transportation studies by Márquez, Macea and Soto (2019), Tsai and Chen, (2019), Lee and Yip (2017), Wen, Wu and Fu, (2017) Yang, Lu and Hsu (2014) and Fleischer, Tchetchik and Toledo (2012).

The orthogonal design allows all attributes to be uncorrelated and attribute levels to be balanced. However, an efficient design method has been used to minimise standard errors in recent years. An efficient design disadvantage is the need for prior knowledge of estimated parameters. This makes the experimental design sensitive to a misspecification of previous parameters. Choosing an orthogonal design reflects our preference for statistical independence over efficiency.

Table 2. Attributes and levels

Attribute	Levels	Alternatives			
		VVC	AVA	AAL	CMP
Round-trip fare *	0	P_{VVC}-20%	P_{AVA}-20%	P_{AAL}-20%	P_{CMP}-20%
	1	P_{VVC}	P_{AVA}	P_{AAL}	P_{CMP}
	2	P_{VVC}+20%	P_{AVA}+20%	P_{AAL}+20%	P_{CMP}+20%
Travel time	0	3.5 hours (non-stop)			
	1	6 hours (one-stop)			
	2	8.5 hours (one-stop)			
Flight frequencies	0	1 flight/day	6 flights/day	1 flight/day	5 flights/day
	1	2 flights/day	7 flights/day	2 flights/day	6 flights/day
	2	3 flights/day	8 flights/day	3 flights/day	7 flights/day
Arrival time_MIA	0,1,2	Morning: 6 a.m., 9 a.m., 12 noon			
	0,1,2	Afternoon: 1 p.m., 4 p.m., 7 p.m.			
	0,1,2	Night: 8 p.m., 11 p.m., 2 a.m.			
Departure time_MIA	0,1,2	Morning: 6 a.m., 9 a.m., 12 noon			
	0,1,2	Afternoon: 1 p.m., 4 p.m., 7 p.m.			
	0,1,2	Night: 8 p.m., 11 p.m., 2 a.m.			

* Round-trip fare varies with schedule combinations and purchase days prior to departure day

A full factorial design for four airlines described by five attributes, each of which is further described by three attribute levels, produces 3^{4x5} possible combinations. An orthogonal fractional factorial design was applied to reduce the huge number of combinations into a manageable size using NGENE software (ChoiceMetrics, 2014). The smallest possible experimental design consists of 64 treatment combinations. Four scenarios were identified as dominant options. Furthermore, a block design was used to split the remaining 60 scenarios into 10 subsets to limit respondent burden, thus each respondent needed to assess only six randomly assigned subsets. A pilot study of 60 members was performed prior to full administration of the survey to detect potential problems regarding factors such as questionnaire length, respondent fatigue and survey clarity.

5. Data
This section describes the process used to obtain the data and assesses our analysis database's representativeness.

5.1. Sample size
Cochran (1977) developed the following expression to calculate the sample size for an infinite population

$$n = \frac{z^2 pq}{e^2} \tag{7}$$

where *n* is the sample size, *p* is the estimated proportion of an attribute present in the population, *q* is calculated as *1-p* and *z* represents the z-value that accumulates a probability in the standard normal distribution of α/2, where (1-α) x 100% is the confidence level. In this research, the population is assumed to be a large population with an unknown degree of variability. We assumed the extreme case, where *p* and *q* are both 0.5 and taking 95% as the confidence level with ±5% precision. Thus, the sample size (*n*) is 384. In our research, we decided to conduct at least 480 surveys (*n* + 96) because of the probability of inconsistent or missing data.

In order to draw a representative sample of all air passengers and reflect the real airline usage pattern for the MDE-MIA journey, quota sampling was necessary for the surveys. Table 3 is based on relative frequencies of airlines market share and the sample size found by equation 7. The total sample was stratified by sample size in each category, as shown in

Table 3. Therefore, the data employed in this study may be representative of the population of customers in the MDE-MIA journey.

Tab 3. Sample rate based on airlines market share

	MDE - MIA journey market share		
Carrier	Population	Relative Frequency	Collected sample
VVC	30,410	19.6%	95
AVA	43,084	27.7%	130
AAL	74,047	47.6%	225
CMP	7,907	5.1%	30
Total	155,448	100.0%	480

5.2. Data collection
Surveys were performed face-to-face since the scientific literature indicates that this sampling method delivers better results in terms of representativeness (Szolnoki and Hoffmann, 2013). Data were collected at MDE airport, near the international flight boarding gate. Passengers who travelled to MIA airport were asked to fill out the questionnaire. All MDE-MIA flights over October and November 2018 were sampled. Passengers who were travelling as part of tourist packages were excluded as they would not be aware of the air travel portion of their cost.

The questionnaire consisted of four sections. In the first section, travellers were asked about socioeconomic characteristics, such as age, gender, individual monthly income, education level and employment status. The second section collected information on traveller experience, including air trip frequency, journeys taken over the last year by each airline, membership in FFP, airline chosen for the last international flight and airline chosen for the last domestic flight. In the third section, passengers were asked about their current trip, including the airline chosen for the MDE-MIA-MDE trip, the number of connections, airfare paid, trip purpose, the number of people flying together, who paid the trip and ticket payment method. In the last section, prior to the SP experiment, passengers were asked about preferred arrival and departure schedules (to and from MIA) and the number of days prior departure that the flights were booked. These questions provided information needed to assign travellers to a specific

type of questionnaire related to schedule combinations and airfare. Respondents conducted six SP games in which each respondent chose one alternative among four air carriers. Fig 3 shows an example of the choice card presented to the respondents.

5.3. Data description

The travellers interviewed yielded 480 valid responses. Table 4 shows that the gender representation within the sample was relatively balanced with 43.8% male and 56.2% female. The 21- to 40-year-old age group composed 59.8% of the sample, 71.3% possessed at least an undergraduate degree, 46.9% were salaried workers and 15% of the travellers had personal monthly incomes of more than 2168 USD. In terms of trip characteristics, 75.2% of the respondents were travelling for non-business, the average number of trips during the previous year was 5.75, and travellers booked their tickets an average of 32 days before the flight. Approximately 41.2% of the travellers had membership in an FFP such as LifeMiles (AVA), AAdvantage (AAL), or MileagePlus (CMP). In terms of schedule preference, 27.5% of passengers preferred to arrive at MIA in the morning and depart from MIA in the afternoon for the return flight. That schedule combination represents the largest percentage of traveller preferences. Loyalty was defined as the percentage of the passengers who chose AVA, AAL, VVC, or CMP for the MDE-MIA-MDE trip and also chose the same carrier in the SP experiment. The highest loyalty percentage is 27.1 for CMP airline, followed by 25.2 for AAL and 21% for the VVC low-cost carrier. This percentage confirmed that passengers who choose low-cost carriers could prefer other airlines depending on attributes levels.

6. Model estimation and empirical results

Multivariate outlier detection is an important task in statistical analysis. A classical approach for detecting outliers in a multivariate framework is Mahalanobis distance (MD). We used MD to find the outliers in the sample using SPSS software (Pérez, 2004). The MD score for each subject is considered an outlier if it exceeds a critical value. The probability level set for this test was $p < 0.01$. The MD method was applied to illustrate multiple outliers. The dataset for international flights contained 480 respondents, with only seven outliers identified using the MD ($p < 0.01$). Therefore, the new sample size for modelling was 473 respondents.

To explore choice behaviour, we applied the MNL (equations (1) to (4)) and ML (equations (5) and (6)) models. The dataset contained 2838 observations. Estimation was performed using BIOGEME software and numerous specifications were tested. We identified that FREQ was not significantly different from zero at the 0.1 level in the first estimations. Therefore, we used the log-transform for FREQ. The log-transform has been widely used by Seelhorst and Liu (2015), Hess, Adler and Polak (2007), Theis *et al.* (2006) and Hess and Polak, (2005), suggesting that a non-linear transformations approach leads to significant model performance improvements.

To verify the presence of endogeneity, we implemented a two-stage least squares instrumental variable model (Greene, 2003). First, we used a diagnostic test to verify that the Hausman-type instrument is valid. The result of the ordinary least squares regression for the Hausman instrument indicates that the parameter associated with the airfare instrument is significantly different from zero at a 95% confidence level. Finally, we tested the null hypothesis that airfare is an exogenous regressor using the t-statistic associated with the residual. The result was not significant at the 0.05 level, thus the null hypothesis was not rejected, indicating that airfare should not be treated as endogenous. Therefore, endogeneity was not present in our model.

Table 5 lists the results of the MNL and ML models. The MNL_1 and ML_1 models do not include both return flight attributes (Y_{in}) and attributes related to the interaction between outbound and return flight variables (Z_{im}). The final versions of MNL and ML include all parameters set out in equation (2). Additionally, the panel effect was taken into account given that responses of the same individual to an SP survey may be correlated, thus it is necessary to include an additional term for panel effect (Cantillo, Ortúzar and Williams, 2007).

Attributes	**VVC**	**AVA**	**AAL**	**CMP**
Flight frequencies	2 flights/day	7 flights/day	3 flights/day	5 flights/day
Travel time	8:30 hours (one-stop)	6:00 hours (one-stop)	3:30 hours (non-stop)	3:30 hours (non-stop)
Airfare	346 USD	449 USD	702 USD	821 USD
Arrival schedule to MIA	07:00 p.m.	04:00 p.m.	04:00 p.m.	01:00 p.m.
Departure schedule from MIA to MDE	06:00 a.m.	09:00 a.m.	12:00 noon	09:00 a.m.

Fig. 3. Sample choice scenario based on booking seven weeks prior to departure day and A-M schedule preference

Table 4. Analysis of simple structure

Variable	Category	Frequency	Percentage (%)
Gender	Male	210	43.8
	Female	270	56.2
Age (years)	18-30	147	30.6
	31-40	140	29.2
	41-50	91	19.0
	51-60	73	15.2
	61 and over	29	6.0
Employment status	Salaried worked	225	46.9
	Self-employed	116	24.2
	Student	62	12.9
	Housewife or unemployed	52	10.8
	Retired	25	5.2
Education	Less than Undergraduate	138	28.7
	Undergraduate degree	263	54.8
	Postgraduate	79	16.5
Monthly income*	0-33	75	15.6
	34-274	43	9.0
	275-667	61	12.7
	668-1167	98	20.4
	1168-1667	80	16.7
	1668-2167	51	10.6
	>2168	72	15.0
Frequent Flier Program membership	Membership	198	41.2
	Non-membership	282	58.8
Travel purpose	Non-business	361	75.2
	Business	119	24.8
Schedule preference	MM	101	21.0
	MA	132	27.5
	MN	32	6.7
	AM	55	11.5
	AA	88	18.3
	AN	13	2.7
	NM	14	2.9
	NA	9	1.9
	NN	36	7.5
Loyalty	AVA	-	15.8
	AAL	-	25.2
	VVC	-	21.2
	CMP	-	27.1

*USD

Table 5. Estimation results for multinomial logit (MNL) and mixed logit (ML) models

Variable	Alternative	Estimate (t-value)			
		MNL_1	MNL_final	ML_1	ML_final
ASC 1	AVA	1.360 (9.68)***	1.260 (8.20)***	1.53 (9.53)***	1.420 (8.07)***
ASC 2	AAL	1.180 (8.35)***	1.070 (6.89)***	1.30 (6.13)***	1.170 (6.68)***
ASC 4	VVC	0.798 (5.33)***	0.646 (3.99)***	0.853 (5.07)***	0.706 (3.87)***
Travel Time (TTIME)	ALL Mean	-0.244 (-20.54)***	-0.245 (-20.55)***	-0.328 (-14.49)***	-0.330 (-14.49)***
	SD			0.379 (8.12)***	0.382 (8.13)***
Round-trip fare (FARE)	ALL Mean	-0.307 (-13.71)***	-0.313 (-13.89)***	-0.380 (-11.76)***	-0.391(-11.85)***
	SD			0.289 (3.04)***	0.294 (3.07)***
Arrival schedule time difference (ARR)	ALL	-0.034 (-2.57)***	-0.036 (-2.71)***	-0.034 (-2.28)**	-0.037 (-2.44)***
Departure schedule time difference (DEP)	ALL		-0.031 (-2.25)**		-0.038 (-2.34)**
Travel purpose (PURPOSE)	AAL-AVA-VVC	0.485 (1.92)*	0.521 (2.05)**	0.495 (1.71)*	0.544 (1.86)*
FFP membership (FFP)	AAL-AVA-CMP	0.873 (7.20)***	0.861 (7.06)***	1.11 (8.24)***	0.991 (7.07)***
Age (>61) (AGE5)	AAL	0.836 (4.67)***	0.861 (4.79)***	0.947 (4.41)***	0.981 (4.55)***
Postgraduate degree (EDU4)	AAL-AVA-CMP	0.430 (2.41)**	0.449 (2.50)***		0.528 (2.59)***
Morning-Afternoon (MA)[a]	AVA-VVC-AAL		0.497 (2.02)**		0.571 (2.00)**
Afternoon-Night (AN)[a]	CMP-VVC		1.230 (4.66)***		1.410 (4.66)***
Night-Morning (NM)[a]	AAL		0.515 (1.91)*		0.561 (1.76)*
Panel effect	AAL-AVA-VVC	1.730 (13.35)***	1.74 (13.40)***	1.98 (12.67)***	1.990 (12.76)***
Log-likelihood at convergence		-3299.457	-3282.558	-3283.731	-3263.335
Rho-square		0.136	0.137	0.140	0.146

***significant at 1%, **significant at 5%, *significant at 10%
[a] Arrival schedule to MIA-Departure schedule from MIA

6.1. MNL model results

As expected for models in Table 5, the coefficient estimates for TTIME, FARE, ARR and DEP had negative signs. Travel time is considered a fundamental factor in both transport modelling and economic appraisal (Juhász, Mátrai and Koren, 2017). The model shows that the t-value was the highest (t-value = −20.55) for TTIME in the MNL_final model, indicating that this attribute has the highest statistical significance in the model and that higher TTIME values would reduce the probability of choosing an airline. FARE also has a negative relationship with airline utility. Based on statistical significance levels, FARE was the next most significant attribute in the model.

ARR has the expected negative effect on airline utility and was significantly different from zero at the 5% significance level. Furthermore, we found that DEP for the return flight is a significant driver in airline choice; however, this effect is smaller in magnitude than ARR. Several observations can be made from the results of schedule difference variables in Table 5. First, as expected, passengers prefer itineraries that get them to their destination close to their preferred time of arrival. Second, travellers were primarily concerned about ARR rather than DEP. Third, schedule time differences coefficients in both models indicate that when the time difference increases, the utility of travellers decreases. This is intuitive as passengers are likely to have more schedule constraints if they have short stays, and in our research the stay was for two weeks on average. In addition, in our model, schedule time differences did not differentiate between early and late.

The analyses of previous models revealed that the log-transformed frequency's coefficient is positive, meaning that the probability of travellers choosing an airline increases when FREQ increases; however, the log-transformed frequency was not significantly different from zero at the 10% significance level for MNL and ML models. This may simply be due to the fact that travellers choose flight schedules rather than frequencies. Previous studies have shown FFP membership having strong effects on airline choice (Wu and So, 2018); Hossain, Saqib and Haq, 2018; Seelhorst and Liu, 2015; Park, 2010; Proussaloglou and Koppelman, 1999). This finding is reinforced in the current research. The FFP membership coefficient is both highly significant and positive, indicating that travellers prefer flying with an airline with which they have FFP membership. In terms of travel purpose, the coefficient was also positive, indicating that respondents on business trips have a higher probability of choosing AAL, AVA or VVC airlines. The reason may relate to CMP airline currently not offering non-stop flights from MDE to MIA. Freund-Feinstein and Bekhor (2017) stated that business travellers are willing to pay more for non-stop flights. As indicated earlier, travellers were asked about their arrival and departure schedule preferences, and the MNL_final and ML_final models show a positive impact of MA, AN and NM schedule interactions on airline utility. MA schedule interactions preference significantly affect AAL, AVA and VVC airline choice, whereas the AN interaction preference significantly affects CMP and VVC airline choice.

Table 5 indicates the statistical significance of DEP and flight schedule combinations in the models with return flight attributes. We applied the likelihood ratio test to compare the models shown in Table 5. The MNL_1 and MNL_final models can be formally tested by using the likelihood ratio test that is expressed as (Ben-Akiva and Lerman, 1985):

$$-2[LL(\beta_{restricted}) - LL(\beta_{unrestricted}] \sim \chi^2_{Number\ of\ restrictions} \quad (8)$$

The test value is -2(- 3299.457 3282.558)=33.798, which is substantially larger than χ^2 value with four degrees of freedom at any reasonable level of significance. Thus, the null hypothesis that departure flight schedule preference for the return flight and

the schedule interactions do not play a role in airline choice can be strongly rejected.

6.2. ML model results

After estimating MNL models both without and with return flight attributes and flight schedule combinations, random coefficients were considered based on travel time and airfare. The final specifications of the ML model were based on eliminating statistically insignificant variables. Functional forms were tested, including linear effects, dummy variable effects and logarithmic transform effects for FREQ. In the first models, the standard deviation of FREQ, ARR and DEP were not significant, whereas the other variables had significant standard deviations. The final ML specification was selected based on statistical fit. Table 5 shows the final results of ML estimation considering normal distributions for the random coefficients. Thus, the final ML model indicates random taste variation only for TTIME and FARE.

The models ML_1 and ML_final can also be compared using a likelihood ratio test. The likelihood ratio test value is 40.792, which is higher than the χ^2 table value with 5 degrees of freedom at even the 0.001 level of significance. Thus, even in the ML framework, the null hypothesis that departure flight schedule preference for the return flight and the round-trip flight schedule interactions do not play a role in airline choice can be strongly rejected.

The above analysis shows that models with attributes related to return flight and its interaction with outbound flight attributes have a superior fit compared with models only based on attributes reported in the literature review (models without return flight attributes and the schedule interaction between round-trip flights). Therefore, the research contributions are significant and improve the knowledge of factors that influence airline choice behaviour.

The likelihood radio test suggested that ML_final had a superior goodness of fit to that of MNL_final model, meaning that ML_final has the best fit and is thus the preferred model ($i.e.$, $38.446 > \chi^2_{0.05}(2) = 5.9915$). This highlights the importance of introducing random taste variations.

Table 5 shows that the panel effect is highly significant, meaning that the ML_final model enables the capture of intrinsic correlations among observations from the same traveller. Furthermore, the absolute value of the log-likelihood at convergence is

3263.335, which is smaller than the absolute value of 3403.835 obtained using the ML model without a panel term.

The ML_final model can be expressed as follows:

$$
\begin{aligned}
U_{\{VVC\,AVA\,AAL\,CMP\}} = \\
1.42\,\mathrm{I}_{\{AVA\}} + 1.17\,\mathrm{I}_{\{AAL\}} + \\
0.706\,\mathrm{I}_{\{VVC\}} - 0.330 * TTIME - \\
0.391 * FARE - 0.037 * ARR - \\
0.038 * DEP + 0.544\,\mathrm{I}_{\overline{\{CMP\}}} * PURPOSE + \\
0.991\,\mathrm{I}_{\overline{\{VVC\}}} * FFP + 0.981\,\mathrm{I}_{\{AAL\}} * AGE5 + \\
0.528\,\mathrm{I}_{\overline{VVC}} * EDU4 + 0.571\,\mathrm{I}_{\overline{\{CMP\}}} * MA + \\
1.410\,\mathrm{I}_{\{VVC\cup CMP\}} * AN + 0.561\,\mathrm{I}_{\{AAL\}} * NM
\end{aligned}
\tag{8}
$$

6.3. Sensitivity analysis

This research used ML model results to conduct a sensitivity analysis considering the impacts of TTIME, schedule combinations, travel purpose and FFP membership. A case strategy scenario is determined by multiplying the appropriate β_k from Table 5 by each attribute's value. This represents the deterministic portion of the utility function (V_i) (Ortúzar and Willumsen, 2011). The results obtained produce overall choice probability for any given value. The ML model considers random coefficients; therefore, market shares are computed by simulating the distribution of random coefficients.

Table 6 reports the change in market shares concerning different travel times, as well as the assessment of different schedule combinations considering if travellers are business passengers with or without FFP membership. For all individuals, the values of TTIME, FARE, ARR and DEP were based on the choice experiment. If passengers are for business purposes, travellers book tickets three weeks before the trip on average. Therefore, airfare for this kind of passenger was based on a booking time of three weeks for each schedule combination.

The base scenario when travellers are business passengers reported in Table 6 shows that CMP currently offers one-stop flights (6 hours), whereas AVA, AAL and VVC all have non-stop flights (3.5 hours). Table 6 also shows that airline choice probabilities are influenced by TTIME. In fact, shifting TTIME to the best attribute level (non-stop flight) could produce an increase of 12% (18%-6%) in

CMP airline choice probability. This probability increase is achieved for travellers having an FFP membership and preferring to fly in AN schedule combinations (case 3 and case 4). Table 6 also reports that airline choice probabilities for AVA, AAL and CMP are influenced the most by the FFP membership strategy. Case 2 corresponds to the analysis of a non-stop flight for each airline with MA schedule combination preference, thus if passengers have an FFP membership, the AVA, AAL and CMP choice probabilities would increase by 10% (37%-27%), 7% (26%-19%) and 4% (11%-7%), respectively, compared with passengers without an FFP membership. The sensitivity analysis for non-business passengers is shown in Table 7. For these travellers, airfare was based on a booking time average of five weeks. As in Table 6, case 3 shows that VVC, AVA and AAL airlines provide non-stop flights, whereas CMP offers one-stop flights. If CMP airline would offer non-stop flights (case 4), approximately 28% of passengers who have FFP memberships and prefer AN schedule combinations, would choose CMP, increasing from 10% to 28% with respect to one-stop flights. As expected, there is an increasing likelihood that travellers tend to choose an airline when it offers non-stop flights. In order to supplement sensitivity analysis, Fig 4 reports the seven policies with the greatest impact on each air carrier choice probabilities. The results were estimated by shifting the level of each attribute from the actual one to the best possible thus providing relevant information regarding the priority that should be assigned to each strategy given its positive impact. Fig 4 shows that airline choice probabilities in the case of VVC and CMP are influenced the most by the AN and NM schedule preference combination, increasing airline choice probability by 29.6% and 10.8%, respectively. TTIME represents the second most important strategy instrument for CMP that would produce an increase of 10.0% in choice probability if CMP would offer non-stop flights. On the other hand, AAL and AVA would increase their choice probability the most by intervening airfare strategy. In fact, reducing airfare by up to 30% would respectively increase airline choice by 35% and 32.2%.

Table 6. Changes in market shares based on business passengers

Scenario						Probability (%) to be chosen if traveller has							
	Travel time (hours)				Schedule combina-	Non-FFP membership				FFP membership			
Case	VVC	AVA	AAL	CMP	tion preferences	VVC	AVA	AAL	CMP	VVC*	AVA	AAL	CMP
Base	3.5	3.5	3.5	6	MA	50	28	20	2	28	40	29	3
2	3.5	3.5	3.5	3.5	MA	47	27	19	7	26	37	26	11
3	3.5	3.5	3.5	6	AN	53	26	17	4	30	39	25	6
4	3.5	3.5	3.5	3.5	AN	49	23	15	13	26	34	22	18
5	3.5	3.5	3.5	6	NM	24	42	32	2	10	49	38	2
6	3.5	3.5	3.5	3.5	NM	23	40	31	7	10	46	36	9

* non-FFP membership for VVC

7. Discussion

In this research, we investigated the effects of schedule combinations on airline choice using MNL and ML models. The ML model results indicated that MA could produce the highest choice probability for AVA; whereas for AAL, NM schedule interaction increases its choice probability. For VVC and CMP, AN schedule combinations increase their choice probabilities. Hence, offering an FFP membership, non-stop flights and MA, NM and AN schedule combinations are the most effective strategies to increase market share. The ML model results also showed that ARR and DEP have negative and significant impacts on the utility of airlines. We also identified that ARR and DEP have similar effects on the utility of airlines for international trips. We determined that random heterogeneity exists for TTIME and FARE. Like previous study of round-

trips by Theis *et al.* (2006), the analysis presented in this research has highlighted the important role airfare plays in airline choice. The results from this SP study have shown TTIME to be the variable with the most explanatory power for an international round-trip flight. The analysis also revealed significant effects in response to FFP. ML model results indicate that FFP membership is a strong driver of airline choice. We can conclude that we do find evidence that some travellers who have FFP membership with at least one air carrier tend to place little focus on FFP membership when choosing airlines. Therefore, airline marketing managers should carefully design benefits provided by FFP membership, as an efficiently developed FFP membership might improve competitive advantage by retaining loyal travellers, which becomes a source of steady revenue.
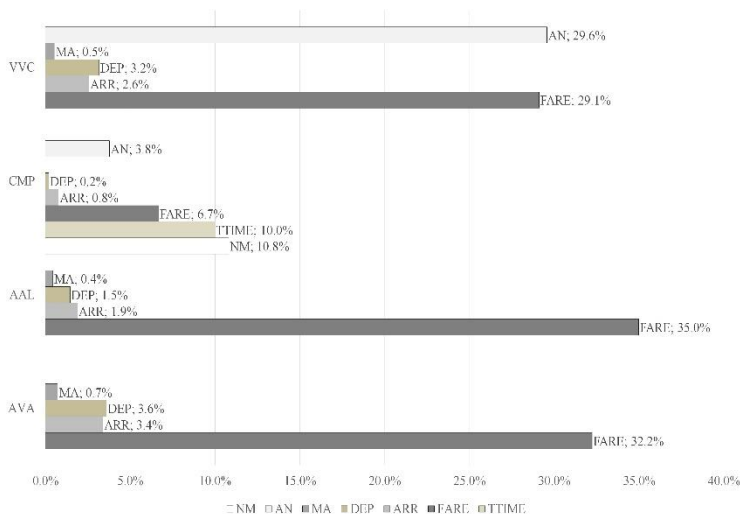

Fig. 4. Variation of airline choice probabilities as a function of attributes variation

Table 7. Changes in market shares based on non-business passengers

Scenario						Probability (%) to be chosen if traveller has							
	Travel time (hours)				Schedule combina-	Non-FFP membership				FFP membership			
Case	VVC	AVA	AAL	CMP	tion preferences	VVC	AVA	AAL	CMP	VVC*	AVA	AAL	CMP
Base	3.5	3.5	3.5	6	MA	38	31	30	2	19	40	39	2
2	3.5	3.5	3.5	3.5	MA	36	30	28	6	18	38	37	8
3	3.5	3.5	3.5	6	AN	42	34	18	7	21	46	24	10
4	3.5	3.5	3.5	3.5	AN	35	28	15	22	17	36	19	28
5	3.5	3.5	3.5	6	NM	20	55	23	3	8	63	26	3
6	3.5	3.5	3.5	3.5	NM	19	52	22	8	8	59	24	9

* non-FFP membership for VVC

8. Conclusion

This study contributes to the literature by introducing the effect of schedule preferences on airline choice for a round-trip flight. Return flight schedule preference had not been covered by other studies within this field. Problems with departure schedule preferences in the return flights could be mitigated if an airline could increase flight frequency to reduce the difference between preferred and offered departure times and thus improve passenger welfare.

This paper discussed the findings of research making use of innovative survey design for understanding air passenger travel choice behaviour. In the survey design, airfare for the international round-trip flight was the result of fare combinations depending on schedule interactions and number of days prior to departure day flights was booked. This design improves realism on how people handle airline choice context for round-trip travel. The model results clearly demonstrate the importance of arrival and departure schedules as well as schedule combinations. In addition, our study's results indicated passenger preference for flying non-stop. In keeping with this, air carriers could design alternative travel arrangements using the proposed model to improve travellers' perception and not affect their loyalty.

The strategy implications deriving from this research can be distinguished in two main categories: one general and one specific to the case study analysed. The study conducted reveals that, in general, one cannot a priori assume that similar policies will produce similar effects in different airlines. With specific reference to the four air carriers studied one can say that the most relevant strategy attributes influencing choice probabilities are TTIME, FARE, ARR, DEP and schedule preference combinations. The results reported in this paper can be extended and improved by acquiring detailed information concerning travellers satisfaction with airline service quality in order to increase model explanatory power.

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