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Passenger airport choice decisions in a multi-airport region in South Africa

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Abstract

Airports in a multi-airport region (MAR) have to compete for passengers and the airport choices of these passengers depend on a number of explanatory variables. This research investigated the airport choice behaviour of domestic passengers in a South African MAR by determining their sensitivity to different choice attributes.

For this purpose, a discrete choice approach based on stated preference data was used to identify the preferences of departing passengers from two neighbouring airports. The questionnaire was based on a Bayesian efficient (D-optimal) design with 60 choice sets. Computer aided personal interview (CAPI) surveys at each of the airports resulted in 6180 records. In order to account for preference heterogeneity a Latent Class Model (LCM) was calibrated taking into account access time, access cost, air fare, parking cost, parking time, flight frequency and flight delays.

The model estimation results reflected the preference heterogeneity with three classes exhibiting different sensitivities to choice attributes. Class willingness-to-pay (WTP) measures indicate that passengers were inclined to accept a higher value for travel time savings to the regional airport.

Key phrases

Airports; airline demand; discrete choice; Latent Class Model and low-cost airlines

1. INTRODUCTION

The Greater Johannesburg region, situated in the Gauteng province of South Africa, has one major international airport, Oliver Tambo International Airport (ORTIA) and a number of smaller regional airports. These regional airports include: Lanseria International Airport (LIA), Grand Central (GCJ), Rand (QRA) and Wonderboom (PRY). ORTIA provides a mixture of long- and short-haul services and is served by a combination of full-service scheduled carriers and low-cost carriers (LCCs). ORTIA is owned and managed by die Airports Company South Africa (ACSA) which is majority owned by the South African Government. LIA on the other hand, is privately owned and is served by charter airlines and LCCs. LIA is situated west from Johannesburg and is approximately 55 kilometres from ORTIA, which is located to the east of the city.

Three LCCs (Kulula.com, Mango and FlySafair) offer domestic services from LIA to Cape Town International Airport (CIA) and Durban International Airport (DIA). These airlines offer similar domestic services from ORTIA. In addition, other full cost carriers (FCCs) also operate from ORTIA namely SAA and BA. These two airports have to compete for passengers since a passenger departing from the greater Johannesburg area to either Cape Town or Durban has the option to use any one of these two airports. However, these airports have different characteristics in terms of services and costs, the one (ORTIA) being a major international airport and the other (LIA) being a smaller, regional airport. The opposite also applies since a passenger departing form either Cape Town or Durban could choose any one of the airports as destination.

Metropolitan areas with more than one airport are referred to as multi-airport regions (MAR) and airports in these regions have to compete for passengers. The competition between airports may result in traffic leakage which occurs when passengers use airports not in their region to take advantage of cost and service benefits (Lian & Rønnevik 2011:85).

Traffic leakage is a function of airport and airline characteristics such as access time and cost and air fares. Several studies have been carried out to model a passenger's choice in a multi-airport region (Lian & Rønnevik 2011:86). Although the specific objectives of the different studies may vary there are two common themes amongst this research:

- Passenger preferences with regards to airport choice in a multi-airport region are important to the stakeholders and it is important to understand the sensitivity of passenger choices to exogenous variables.

- Discrete choice analysis, specifically the stated preference approach has been applied successfully to model passenger airport choice.

The purpose of this research was to develop a stated preference model that could explain the impact of airport and airline characteristics on the airport choice (ORTIA and LIA) of passengers departing from the greater Johannesburg region to Durban and Cape Town.

2. LITERATURE REVIEW

2.1 Airport competition

An increase in air traffic worldwide has been observed as a result of many changes in the industry such as the liberalisation of the air transport markets which resulted in the emergence of low cost carriers (Luke & Walters 2013:3). The increase in the low cost carrier segment has had a significant impact on the airport business. This resulted in increased pressure on primary airports and, subsequently, in a shift by the low cost carriers to secondary airports where available (Barrett 2004:33). In these situations airports and airlines compete and the impact on the passenger is as follows (Jimenez, Claro & Pinho de Sousa 2014:949):

- air fares;
- access time and cost; and
- destinations offered.

In such an environment it is crucial that airport and airline management understand the impact of airport and airline characteristics on the airport choice of passengers.

2.2 Passenger air travel choice analysis

Various studies over the years have used discrete choice models in the analysis of air travel choice behaviour (Bergantino, Capurso & Hess 2017:2; Jung & Yoo 2016:70; Cho, Windle & Dre 2015:140; Yang, Lu & Hsu 2014:89 and Hess, Adler & Polak 2007:221). This approach allows researchers to understand how respondents value certain choice attributes (Mangham, Hanson & McPake 2009:152). Individuals make decisions by comparing alternatives and selecting an action and these decisions are subject to a large amount of variability (heterogeneity). This is based on the fact that it is an individual's level of preference for a specific alternative that determines which choice will be selected (Hensher, Rose & Green 2015:21).

Discrete choice models may be based on two types of data: revealed preference (RP) or stated preference (SP) (Roh 2013:45). RP data reflects the reality as opposed to SP data that reflects hypothetical situations which may not be reflected in the RP environment. Hess *et al.* (2007:221) found that modelling airport choice with stated preference (SP) data results in more significant parameter estimates than revealed preference (RP) data.

The multinomial logit model (MNL) has been the most frequently used to model respondents' choices (Roh 2013:45; Greene & Hensher 2003:681 and Cheng & Long 2007:583). However, as a result of the basic limitation of the MNL model i.e. the assumption of the independence of irrelevant alternatives (IIA), many modelling innovations have been developed to improve model flexibility (Greene & Hensher 2003:682).

Approaches such as the mixed logit model and the latent class model have also been used to account for preference heterogeneity (De Bekker-Grob, Rose, Donkers, Essink-Bot, Bangma & Steyerberg 2013:534).

2.3 Factors influencing airport choice

Pels, Nijkamp and Rietveld (2003:79) found that business passengers in the San Francisco Bay area were more sensitive to travel time, one of the determining factors in the competition between airports. Başar and Bhat (2004:902) used a probabilistic choice set multinomial logit approach to study passengers' airport choice in the San Francisco Bay area and found that access time and flight frequency were the primary determinants of airport choice. The San Francisco Bay data was also used by Ishii, Jun and Van Dender (2009:225) to estimate a mixed logit model of passenger airport choice. It was found that passengers do not choose an airline and airport, but rather an airport-airline combination. Ishii *et al.* (2009:225) also found that the purpose of travel influences the airport-airline choice.

De Menezes and Vieira (2008:1) used a stated choice approach to model passenger sensitivity to airline attributes on the Azores – Lisbon corridor. The estimated model allowed the researches to calculate willingness-to-pay (WTP) measures for certain attributes. A similar approach was used by Pereira, Almeida, De Menezes & Vieira (2007:26) on the Funchal – Oporto route (Portugal).

Lian & Rønnevik (2011:92) found that air passengers in Norway are prepared to travel large distances to utilize lower air fares and more convenient airline services offered by major airports, resulting in regional airports losing market share i.e. traffic leakage.

Hess (2010:195) established that passengers include complementary information to the information presented to them when making an airport choice. In addition, the distance from the airport significantly influences the passengers' airport choice. Hess (2010:195) found that although passengers in general do not prefer large airports, these airports are selected by passengers, probably due to the perceived wider and higher levels of services.

Ishii *et al.* (2009:219) used attributes such as access time to the airport, air fare, frequency of flights and delays in their research, whereas Hess (2010:192) also included flight time, the availability of connecting flights and the type of aircraft to estimate passengers' sensitivity to airports.

Heyns and Carstens (2011) used factor analysis to determine that the airport decision of passengers departing from ORTIA and LIA in Gauteng is mainly influenced by the following four factors (and associated variables):

- airline efficiencies (on-time arrival/departure, service frequency, departure time);
- airport location & services (time to/from airport, ease of access, ease of check-in);
- safety & security (airport safety, parking security); and
- cost (cost of ticket, cost of parking, cost of getting to the airport).

Stone (2016:162) concluded that quantifiable attributes such as the airfare, total travel time, preferred flight times, as well as reliability may affect passengers' choice of origin airport. Reliability was measured with factors like on-time arrival, delays and flight cancellations (Stone 2016:161).

Air fare, access travel cost and access time were found to be significant in the airport decision in a multi-airport region in Colombia (Munoz, Cordoba & Sarmiento 2017:10). These attributes are in line with most of the research into airport choice.

2.4 Experimental design

A passenger survey is used to obtain the data on the passengers' airport choices for modeling purposes. These surveys are based on experimental designs that reflect the hypothetical choice situations (Bliemer & Rose 2010:720). Each choice situation is a combination of the attributes and attribute levels. In an effort to improve response quality researchers are using the respondent's real trip to frame the choice situations around (Hess 2008:275).

An efficient design can be used to increase the statistical efficiency of the experimental design by minimising the elements of the asymptotic variance-covariance (AVC) matrix of the choice model (Tang, Luo, Cheng, Yang & Ran 2014:3). This allows for more reliable parameter estimations with smaller sample sizes (Tang *et al.* 2014:7). Efficient designs can also be generated by using the respondent's reference as base for the attribute levels (Rose, Bliemer, Hensher & Collins 2008:395). An efficient design based on a respondent's reference is more efficient than the standard orthogonal design, resulting in highly reliable parameter estimates (Tang *et al.* 2014:7).

A crucial aspect of generating an efficient design is prior parameter values and this becomes more complex if the respondent's reference is used (Bliemer, Rose & Hess 2008:100). One approach to deal with prior parameter value uncertainty is to assume a prior parameter distribution i.e. a Bayesian approach (Bliemer *et al.* 2008:100). These prior parameter distributions may be obtained from a pilot study (Bliemer & Rose 2010:71).

2.5 Heterogeneity

Although the basic multinomial logit (MNL) model has been used extensively in the past, the model's assumption of independence from irrelevant alternatives (IIA), which is very restrictive, has resulted in research into approaches that relax this assumption (Greene & Hensher 2003: 681). (The IIA assumption implies that respondents are homogenous). One approach to relax this assumption is the mixed logit model (MMNL) or the random parameter logit model (RPL). Under this model respondent heterogeneity is introduced by allowing parameters to vary according to specified distributions (Ortega, Wang, Wu & Olynk 2011:319).

Another approach to allow for respondent variation is the latent class model (LCM) (Greene & Hensher 2003:682). This approach allows for the preference heterogeneity to occur discretely according to a number of latent classes (Ortega *et al.* 2011:319). Unlike the MMNL model where the parameter distributions have to be specified a-priori, the latent classes are established from the data.

Greene & Hensher (2003:698), as well as Shen, Sakate and Hashimoto (2006:15) have concluded that the LCM performs statistically better than other models on specific data sets in the presence of respondent choice heterogeneity. However, this may depend on the data set's performance under alternative behavioural assumptions (Greene & Hensher 2003:697 & Shen *et al.* 2006:15).

3. METHODOLOGY

3.1 Purpose of research

The purpose of this research was to determine the influence of relevant factors on the decision-making process of domestic passengers departing from either ORTIA or LIA in Gauteng relating to airport choice i.e. estimating passenger sensitivity to different attributes in a multi-airport region (MAR). In addition, a willingness-to-pay value (ratio of access time parameter and access cost parameter) was calculated to evaluate the respondent's value of travel time savings.

3.2 Model design and attributes

A discrete choice approach based on stated preference data was used. Under this approach it is assumed that each choice alternative faced by the decision maker has an associated indirect utility and each of these utilities consists of a deterministic and random component (Munoz *et al.* 2017:4). The deterministic component may be described as a function of the various attributes (Munoz *et al.* 2017:4). The utility may be specified as follows (Hensher *et al.* 2015:45):

$$U_i = V_i + \epsilon_i$$

Where U_i is the overall utility of alternative *i*, V_i is the deterministic component and ε_i refers to unobserved influences (error). The deterministic component may be expressed as follows (Hensher e*t al.* 2015:48):

$$V_i = \beta_{0i} + \beta_{1i} f(X_{1i}) + \beta_{2i} f(X_{2i}) + \cdots + \beta_{Ki} f(X_{ki})$$

Where β_{1i} is the parameter associated with attribute X_1 and alternative *i* and β_{0i} is the constant associated with alternative *i* (there are K attributes).

Based on the literature research, as well as discussions with industry experts, the following attributes were selected to model passengers' airport choice decisions: airline; airline fare; flight delay; airline frequency (# available flights); access mode: (drive self, drop-off, train (ORTIA only), taxi); access time (travel time to airport); access cost; parking cost and time to find parking.

The standard multinomial logit model (MNL) (probability of choosing alternative i) can be expressed as (Hensher *et al.* 2015:97):

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

or

$$Prob_i = \frac{\exp(\beta_i' X_i)}{\sum_{j=1}^{J} \exp(\beta_j' X_j)}$$

Since the MNL model is based on the IIA assumption a latent class model (LCM) was assumed to allow for respondent heterogeneity. For this research a panel latent class model was used since each respondent was required to complete 10 choice tasks. The theory underlying a LCM states that individual choices depend on observable attributes and latent heterogeneity that varies with unobservable factors (Greene & Hensher 2003:682). For the purposes of model identification the class assignment parameters (to be estimated) for one class need to be set to zero (De Bekker-Grob *et al.* 2013:540). This implies that the remaining parameters are interpreted relative to this class.

If J_i alternatives, T_i choice situations and Q classes are assumed then based on the logit model the choice j by respondent i observed in choice situation t (class q) can be expressed as (Hensher *et al.* 2015:708):

$$P_{it|q} = \frac{\exp(x_{it,j}' \beta_q)}{\sum_{j-1}^{J_i} \exp(x_{it,j}' \beta_q)}$$

Where β_q is the parameter vector associated with the vector of explanatory variables $x_{it,j}'$. These probabilities ($P_{it/q}$) are simultaneously estimated with the probability of an individual i being in class q (H_{iq}). The class assignment probability (H_{iq}) is unknown, but may be modelled through a multinomial logit model as follows (Hensher *et al.* 2015:708):

$$H_{iq} = \frac{\exp(z_i' \theta_q)}{\sum_{q=1}^{Q} \exp(z_i' \theta_q)}$$

where z_i represents a set of observable characteristics.

The unconditional probability of choosing alternative i is then (Hensher *et al.* 2015:709):

$$P_i = \sum_{q=1}^{Q} H_{iq} \, P_{i/q}$$

An overall (mean) WTP value can be calculated by using the probability that a respondent belongs to a class as weight for the conditional WTP value ($\frac{\beta_{time/q}}{\beta_{cost/q}}$) as follows (De Bekker-Grob *et al.* 2013:535).

$$WTP = \sum_{q}^{Q} P_q \frac{\beta_{time/q}}{\beta_{cost/q}}$$

3.3 Survey experimental design

According to De Luca and Di Pace (2012:2) many of the estimated airport choice models provide for a broad understanding of airport choice without taking different choice dimensions into consideration. This research was based on a multi- dimensional choice approach by including the passenger's access mode. The stated preference (SP) survey included seven choices (alternatives) relating to the airport (ORTIA and LIA) and mode of access (drive self, drop-off, train, taxi).

A Bayesian, D-optimal efficient (balanced) design with 60 choice sets was generated with Ngene 1.1.1 and the overall design was blocked into 6 subsets with 10 choice sets each (Bliemer *et al.* 2008:100). The a-priori distributions for the parameters were estimated from a pilot survey of 15 respondents. In addition, the pilot study confirmed the validity and acceptability of the questionnaire.

The experimental design was partially based on the respondent's reference i.e. the different levels of certain attributes were varied (pivoted) based on the passenger's current experience (Hess 2008:275). Air fare, access time, access cost and parking cost were pivoted and the other attributes had fixed levels (Table 1).

TABLE 1: Description of the attribute levels

Attribute	**Levels**
Airline	1, 2, 3, 4, 5
Fare	-20%, -10% ,Reference, +10%, +20%
Delay (minutes)	0 min, 15 min, 30 min, 45 min
Frequency (number of flight to choose from)	1, 2, 3, 4
Access time – ORTIA (West)	-15 min, Reference, +15 min
Access time – ORTIA (East)	-5 min, Reference, +5 min
Access time – LIA (West)	-5 min, Reference, +5 min
Access time – LIA (East)	-15 min, Reference, +15 min
Access cost	-20%, -10% ,Reference, +10%, +20%
Parking time – ORTIA	10 min, 15 min, 20 min
Parking time - LIA	5 min, 10 min, 15 min
Parking cost	-20%, -10% ,Reference, +10%, +20%

Source: Based on survey questionnaire

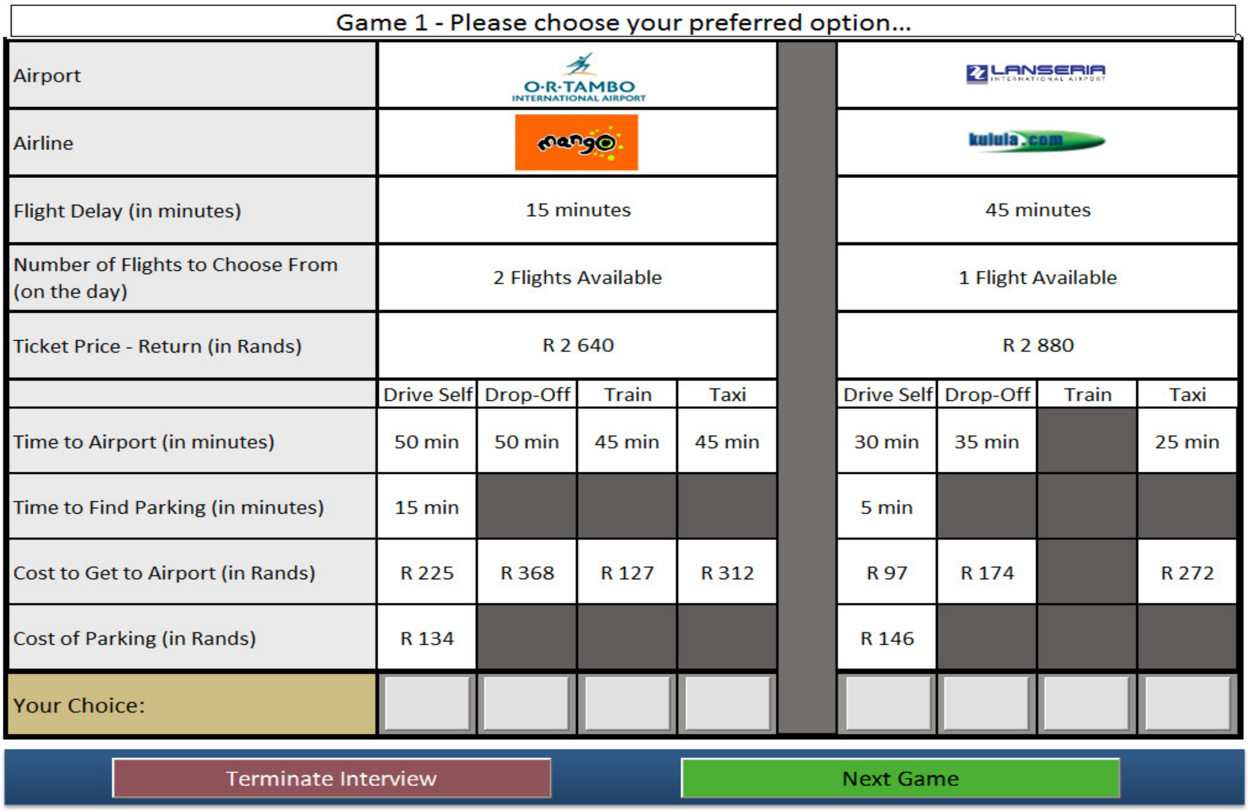
The reference information was obtained at the start of the survey and the subsequent games (choice alternatives) were based on the percentage changes as per the experimental design (Table 1). The access time levels varied according to the trip departure point (geographical location) of the passenger i.e. distance from each of the airports.

3.4 Survey

The study population was the domestic passengers at LIA and ORTIA departing for CIA and DIA and the survey was conducted during February 2013 at these airports. The survey was based on random samples of 312 domestic passengers at ORTIA and 306 domestic passengers at LIA departing for CIA or DIA, each passenger completing 10 choice situations resulting in 6180 records. The samples of passengers at both airports were representative of the day of the week and departure times by the various airlines that were included in the survey.

The survey instrument was based on a computer aided personal interview (CAPI) and an example of the choice screens is displayed in Figure 1.

FIGURE 1: CAPI screen



Game 1 - Please choose your preferred option...

Airport	O·R·TAMBO INTERNATIONAL AIRPORT				LANSERIA INTERNATIONAL AIRPORT			
Airline	mango				kulula.com			
Flight Delay (in minutes)	15 minutes				45 minutes			
Number of Flights to Choose From (on the day)	2 Flights Available				1 Flight Available			
Ticket Price - Return (in Rands)	R 2 640				R 2 880			
	Drive Self	Drop-Off	Train	Taxi	Drive Self	Drop-Off	Train	Taxi
Time to Airport (in minutes)	50 min	50 min	45 min	45 min	30 min	35 min		25 min
Time to Find Parking (in minutes)	15 min				5 min			
Cost to Get to Airport (in Rands)	R 225	R 368	R 127	R 312	R 97	R 174		R 272
Cost of Parking (in Rands)	R 134				R 146			
Your Choice:								

Terminate Interview

Next Game

Source: Based on survey instrument

4. DISCUSSION OF RESULTS

The sample composition (airline, purpose of travel and gender) of the combined survey (ORTIA and LIA) is shown in Table 2:

TABLE 2: Sample composition

Dimension	Description	Percentage
Airline	Kulula.com	36%
	Mango	36%
	SAA	15%
	BA	13%
Purpose of travel	Business	52%
	Visiting friends and relatives (VFR)	23%
	Leisure	17%
	Sports	2%
	Other	6%
Gender	Male	55%
	Female	45%

Source: Calculated from survey data

The majority of the respondents used the two low cost airlines (Kulula and Mango) and the majority of the passengers travelled for business purposes.

The latent class model parameters were estimated with Nlogit Version 5 on the combined data set (ORTIA and LIA). The "best" model as measured by the log-likelihood function and Akaike Information Criterion (AIC) contained three latent classes. Different covariates were included, but the most significant model was obtained with the inclusion of the following covariates:

- Region (West Rand = 1, North Rand= 2, South Rand = 3, East Rand = 4, Sandton Area = 5, Melville Area = 6, Johannesburg CBD = 7, Wynberg Area = 8, Midrand = 9, Centurion = 10, Pretoria East = 11, Pretoria West = 12, Pretoria North = 13, Other = 14)

- Gender (male = 1, female = 2)
- Purpose of travel (business = 1, leisure = 2, VFR = 3, sport = 4, other = 5)
- Access mode to airport (drive self =1, drop off = 2, train = 3, taxi = 4, other =5)

The parameter estimates for the LCM are shown in Table 3.

TABLE 3: LCM parameter estimates

Parameter	Class 1		Class 2		Class 3	
	Estimate	St Error	Estimate	St Error	Estimate	St Error
O1	-5.22557**	2.3039	4.48527***	0.8606	0.8555	26.57541
OAIR	0.01857	0.10597	0.04734	0.06038	0.03561	0.04774
OFARE	-.00100***	0.00025	-.00163***	0.00012	-.00128***	.8716D-04
ODELAY	-0.00341	0.00773	-0.00498	0.0045	-.00685**	0.00348
OFREQ	0.14514	0.13557	.12583*	0.06464	.23007***	0.05391
OATIME	0.00122	0.00939	-.02207***	0.00626	-.03889***	0.00477
OPTIME	-.13306D-04	0.13808	0.00093	0.01982	0.02163	0.13081
OACOST	-.00810***	0.00172	-.01331***	0.00124	-.00751***	0.00046
OPCOST	-0.00219	0.00161	0.00013	0.00027	-0.00721	0.01017
O2	-3.77161***	1.19967	1.22244	0.90427	5.24473	26.38262
O3	-1.52919	1.15406	0.59919	0.89107	1.36822	26.37311
O4	-2.45002*	1.32454	-3.81365	71	-0.84818	26.39239
L1	-0.54634	0.70975	4.89203***	0.65321	3.1993	26.47075
LAIR	-0.21948	0.34158	0.08427	0.17175	0.08319	0.1145
LFARE	-.00234***	0.00026	-.00206***	0.00013	-.00232***	.9432D-04
LDELAY	-0.00633	0.00622	-.03609***	0.0036	-.00720**	0.00303
LFREQ	0.08113	0.13349	0.11295	0.09487	.20548***	0.07531
LATIME	-0.01109	0.00868	-.01314***	0.00283	-.03196***	0.00403
LPTIME	.82072D-04	0.05657	-0.00108	0.02106	-0.10663	0.1042
LACOST	-.00392***	0.00116	-.00521***	0.00083	-.00484***	0.00049
LPCOST	-.00330***	0.00094	0.00046	0.00029	-0.00147	0.00102
L2	-.57291***	0.18358	1.38750**	0.60054	7.18051	26.40876

***, **, * Significance at 1%, 5%, 10% level

Source: Calculated from survey results

The respondents were assigned to the classes up to a probability by the class probabilities of 22.2%, 28.5% and 49.3% for latent class 1, 2 and 3 respectively. The estimated class assignment model estimates were as follows (Table 4).

TABLE 4: Class assignment model estimates

This is THETA(01) in class probability model		
Parameter	**Estimate**	**St Error**
Constant	-4.93740***	0.66409
Region	.08160**	0.0389
Gender	0.06474	0.28729
Purpose	-0.13463	0.11213
Travel	1.71823***	0.22074
This is THETA(02) in class probability model		
Parameter	Estimate	St Error
Constant	6.69206***	0.8214
Region	0.03477	0.04333
Gender	-0.4214	0.4166
Purpose	-.33988*	0.18681
Travel	-4.10088***	0.3147

***, **, * Significance at 1%, 5%, 10% level

Source: Calculated from survey data

The class assignment model is specified as a MNL model and it assigns individuals (respondents) to the different classes. The class assignment model indicates that respondents in Class 1 were more likely to include respondents that departed from the northern regions (Region) and more likely to use a taxi or the train (Travel) to get to the airport compared to the other classes. Class 2 respondents were more likely to be leisure or business travellers (Purpose) that drive self to the airport compared to respondents in Class 3.

The significant parameter estimates in Class 1 related mainly to costs (access cost, air fare and parking cost (LIA only)). The absolute value of the LIA air fare parameter (LFARE) estimate was higher than that for ORTIA (OFARE) implying that passengers using LIA were more conscious of the air fare. The opposite was found for the access cost parameter estimates. A comparison of the ORTIA access cost parameter estimate (OACOST) to the LIA access cost estimate (LACOST) indicated that passengers departing from ORTIA placed a higher premium on access cost compared to LIA. The significance of the parking cost parameter at LIA (LPCOST) is surprising since the class assignment model for this class related mainly to passengers using the taxi or the self-drive option to get to the airport.

Significant parameter estimates in Class 2 represented a combination of cost and time (air fare, access cost, frequency and delay (LIA only)). The magnitudes of the estimated air fare parameter revealed a similar pattern to the Class 1 parameters. Passengers departing from LIA were more concerned about the air fare compared to passengers departing from ORTIA. However, ORTIA passengers were more concerned about the access cost and access time (OATIME) relative to LIA passengers (LATIME). LIA passengers were also concerned about flight delays (LDELAY).

Significant Class 3 parameter estimates reflected the importance of all attributes except parking time and cost at both airports. The access cost and access time parameter estimates reflected a similar pattern as the Class 2 parameter estimates. In addition, LIA passengers were more concerned about delays (ODELAY) compared to ORTIA passengers based on the absolute values of the parameter estimates. Passengers departing from ORTIA were more concerned about the frequency of flights compared to passengers departing from LIA (OFREQ vs LFREQ), which confirms the nature of ORTIA as a major international airport offering a higher frequency of domestic flights compared to LIA.

Table 5 below shows the class willingness-to-pay (WTP) relating to access time for each of the airports.

TABLE 5: Class willingness-to-pay (WTP)

	Class 1	Class 2			Class 3		
Airport/ Attribute	WTP	WTP	Confidence limits		WTP	Confidence limits	
		(Rand/hour)	Lower	Upper	(Rand/hour)	Lower	Upper
ORTIA							
Access Time	N/A	99.49	63.21	135.77	310.71	256.54	364.88
LIA							
Access Time	N/A	151.32	100.73	201.91	396.2	312.97	479.42

Source: Calculated from survey results

*The 95% confidence intervals were calculated from the standard deviations of the individual willingness-to-pay values.

The Class 1 WTP measures for each of the airports could not be estimated since neither of the time parameter estimates were significant. This implied that an overall WTP value (mean) could not be estimated. The estimated WTP measures for class 2 and class 3 indicate that passengers in these classes in general were placing a higher premium on the access time to LIA compared to ORTIA.

5. LIMITATIONS OF THE STUDY

A large proportion of the respondents travelled for business purposes and may not have been personally responsible for the air fare and access cost. This information was not elicited during the survey. Although the questionnaire also included a question regarding income level, the response to this question was particularly poor and could not be used for parameter estimation purposes. The responsibility for the air fare and access cost, as well as income information could potentially further improve the understanding of a passengers' choice of airport.

6. CONCLUSION

For this research a stated preference discrete choice experiment was used to analyse air passengers' airport choice in a multi-airport region in Gauteng based on certain airport and airline attributes. The questionnaire was based on a Bayesian efficient (D-optimal) design with each respondent being required to complete 10 choice tasks. In addition, certain attributes (air fare, access time and access cost) were varied (pivoted) based on the passenger's current experience. The survey was based on a computer aided personal interview (CAPI) and completed at ORTIA and LIA.

The estimation results indicate that passengers, all else being equal, tend to select the departure airport based on access time, access cost, air fare, frequency of flights and delays which is in accordance with other research. However, passenger choice heterogeneity resulted in the estimation of three latent classes. The preference heterogeneity between classes is indicated by the differences of the significant parameter estimates in each class i.e. the respondents belonging to the different classes view the attributes relating to airport choice differently.

The first class (22.2% of the respondents) mainly represented respondents that were price sensitive (air fare, access cost and parking costs). The second class (28.5% of the respondents) represented respondents that were price (air fare, access cost) and time (access time) sensitive relating to ORTIA. In addition, the frequency of the flights played a role in their ORTIA decision. The respondents belonging to the second class also valued price (air fare and access cost), access time and one airline attribute (delays) as important attributes in selecting LIA.

Respondents belonging to the third class (49.3%) valued all attributes important except parking time and parking cost. The frequency of flights from both ORTIA and LIA featured significantly in this class. These parameter estimates are positive indicating that higher flight frequencies were valued more by respondents in class 3 (the majority of the respondents).

Incidentally, none of the respondents in any of the classes placed any significance on the airline in terms of their airport decision. This makes sense since the majority of the respondents (72%) preferred the low cost carriers (LCCs) which operate at both airports. A LCM excluding the airline attribute resulted in a marginal improvement in the AIC measure of the model and similar levels of changes to the parameter estimates. These parameter estimates resulted in estimated WTP measures similar to the WTP estimated from the "full" model (Table 5).

A comparison of the significant parameter estimates in Class 1 indicates that passengers viewed air fare at LIA as having a bigger influence on their airport decision compared to the air fare at ORTIA. The air fare parameter estimates of the airports (ORTIA and LIA) were similar in magnitude in the three classes, but the LIA air fare parameter were consistently larger in magnitude compared to the ORTIA air fare parameter for all the latent classes.

This is not surprising since LIA is used only by the low cost airlines and is in general perceived as having a lower cost.

The influence of the access cost parameter estimate associated with ORTIA in Class 1 is almost double that of the parameter estimate for LIA, as measured by the magnitude of the parameter estimate. This is also apparent for most of the other parameter estimates in Class 2 and Class 3.

The estimated WTP measures for class 2 and class 3 indicated that passengers were in general prepared to pay more for travel time savings (access time) traveling to LIA. In addition, the WTP estimates differed significantly between class 2 and class 3.

The results of the research indicate that discrete choice analysis allowed for the identification of three distinct classes of domestic departing passengers at LIA and ORTIA based on differences in their view of airport choice attributes. Cost (mainly air fare and access cost) and access time were considered in varying degrees as contributors to passengers' choice of airport.

7. RECOMMENDATIONS

Further research is required to establish the influence of the cost (air fare and access cost) responsibility and income on the parameter estimates. This could be achieved by allowing respondents at the start of the survey to indicate whether they are personally responsible for the air fare and access costs which could then be used as a covariate to potentially distinguish between different perceptions. In the cases of passengers being personally responsible for the costs, an effort should be made to obtain accurate information on income levels.

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