Abstract

Stated preference (SP) experiments are becoming an increasing popular survey methodology for investigating air travelers' choices. Analysis of this behavior, which is an element of the demand prediction, helps for a better future planning and development of competing airlines. In this thesis, emphasis is stressed on the stated preferences of passengers in choosing between low cost carriers (LCC) and full service carriers (FSC). Binary logit and probit model and latent class model were employed on primary data collected from departing air passengers at Eros airport and Hosea Kutako International airport in Windhoek - Namibia, to model passengers' stated preferences and examine the determinants of carrier choice between LCC and FSC in Namibia. Major findings show that: airfare, age, income and purpose of travel are significantly important with respect to passenger choice. Furthermore, we observed that passengers have different preferences for different destination regions be it domestic, regional or international. For domestic and regional flights (short haul) they prefer LCC, while for international flights (long haul) they opted for FSC. In addition, majority of the passengers were travelling for business purpose, hence their tickets were bought by their respective employers. Most passengers indicated that they were willing to fly LCC if it was available in

Namibia because of it's low fares. There was an indication that air tickets were not affordable and these are a big concern to passengers. Presumably, if ticket prices can come come down or introduce a LCC in Namibia then many will consider flying. This study concluded that, based on the interviewed passengers' profiles, the best and appropriate carrier in Namibia is a low cost carrier. Introducing a LCC in Namibia might be a viable alternative which may ensure sustainability.

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Finally, I want to thank my family for being always being there for me and supporting me spiritually throughout my life. Your prayers for me were what sustained me thus far.

Dedication

I dedicate my thesis work to my family and friends. A special feeling of dedication to my late father and elder brother. I also dedicate this thesis to the Namibian aviation industry, both service providers and passengers.

Declarations

I, **Alisa Amwaama**, declare hereby that this study is a true reflection of my own research, and that this work, or part thereof has not been submitted for a degree in any other institution of higher education.

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Abbreviations and Acronyms

AIC	Akaike Information Criterion
BIC	Bayesian Information Criterion
CNL	Cross-Nested Logit
EA	Eros Airport
FSC	Full Service Carrier
HKIA	Hosea Kutako International Airport
ICT	Information Communication Technology
LCA	Latent Class Analysis
LCC	Low Cost Carrier
MMNL	Mixed Multinomial Logit
ML	Maximum Likelihood
NAC	Namibia Airports Company
NL	Nested Logit
NLS	Nonlinear Least Squares
RP	Revealed Preferences

SADC	Southern African Development Community
SP	Stated Preference

Chapter 1

Introduction

1.1 Orientation of the study

In airline industry, there exist two different types of carriers; full service carrier (FSC) and low cost carrier (LCC) . Smith and Russell (2005) defines FSC, generally called legacy carriers, as carriers that operate what are referred to as ”hub-and-spoke” systems through which they funnel passengers from different locations into central hubs at major airports and sort the passengers onto connecting flights to their ultimate destinations. Thus, passengers often have to change planes at the hub before flying on to their final destinations. This system provides airlines with a broad network and geographic reach and improved load factors. However, the system can result in inefficiencies because the aircraft arrives in waves, thereby creating congestion, and the aircrafts and crew may have longer waits between flights and there is an expectation of an on-time performance. The airlines are also burdened with the expenses of having to handle connecting passengers at origination, hub and destination.

On the other hand, LCC are airlines formed post-deregulation that offer lower fares and they are characterized by attributes such as direct distribution; reduced in-flight service; high aircraft utilization; internet booking; use of secondary airports; minimum cabin crew; lower wage scales; lower rates of unionization among employees; one class of seating; short ground turn-around times; low tariffs and no loyalty programmes (Doganis, 2001). There is some evidence that LCCs have made in-roads into the business travel market in the sub-Sahara region for example in South Africa and Kenya. However, very little if any are practiced in Namibia. In Southern Africa, LCC are Mango, 1-Time and Kulula Airlines, whereas full cost airlines in Namibia and its' neighboring countries include Air Namibia, South African Airways, South Africa Express, British Airways, Air Zimbabwe and Zambezi Air.

The differences between LCC and FSC may impact the air travelers' choice. In 2005, O'Connell and Williams study shows that air travelers are price sensitive and may not be willing to pay high prices associated with FSCs thus making perpetual losses and impacting business survival. A point in case is Air Namibia, which like other FSC National carriers in the region, has been bailed out of debts several times by the Namibian government because they fail to make profit in the business (The right honorable's response paper, 2013). Studies (Doganis, 2001, Hess and Polak, 2005b) have shown that optimization of profit can be realized by offering travelers' competitive choices- in price and services- packaged for a typical travels' preference. There is still a chance for Namibia to change direction of the air market depending on the typical travelers' preference in the country if flight passengers' preferences are modelled along. This study is therefore motivated from this background.

1.2 Literature Review

Stated Preference (SP) methods are widely used in travel behavior research and practiced to identify behavior responses to choice situation which are not revealed in the market. This section presents a brief review of existing research in the analysis of air travel choice behavior, focusing on the airport and airline choice dimensions (which are looked at in this study). More comprehensive reviews are for example given by Basar and Bhat (2004) and Hess and Polak (2006).

Stated choice models have been developed across a variety of transport applications including aviation i.e. flight choice, airline choice, airport choice, and whether to fly or not (Davidson and Ryley, 2010). Some studies on air travel choice behaviour looked at the choice of airport for passengers departing from multi-airport regions (Doganis, 2001; Davidson and Ryley, 2010; Hess and Polak 2005a).

In the context of airport choice, the focus of the study is to apply models that determine the value individuals put on attributes such as parking and retailing, distance and travel time from home, available flight destinations, flight cost, their expectation of queues at the airport and the trade-off values at which individuals would choose an alternative, competing airport (Davidson and Ryley, 2010). This is of paramount importance to airports and airlines and may lead to; for examples route and facility development and customer service offers. Airports need to know the effect on their infrastructure, parking and retail revenues of each carrier or destination offering. They also need to know what motivates passengers' preferences to desire to fly from their airport (perhaps to another competing airport), and the factors that may reduce revenue per passenger.

Recent examples of such studies include the work of Pels et al. (2001), Pels et al. (2003), Basar and Bhat (2004), Hess and Polak (2006a), Hess and Polak (2005a) and Hess and Polak (2005c), who all use data collected in the San Francisco Bay area. These studies make use of various modelling approaches, including nested logit (NL), mixed multinomial Logit (MMNL), and choice set generation models, and generally account for the additional choices along either the airline or the access-mode dimension. Another example of a recent study of airport choice behavior is given by Hess and Polak (2005b), who look at the combined choice of airport, airline and access-mode in the Greater London area, using cross-nested logit (CNL) models.

Stated and revealed preference have been mainly used to interpret the determinants of the underlying choice process and/or to understand the significance of behavioural heterogeneity. The common point across many revealed preferences (RP) studies are the difficulties in retrieving significant effects for air fare, along with many other factors that conceivably play a role in choice behavior, such as the membership in frequent flier programmes. Aside from being partly linked to the often low quality of auxiliary data, especially for fare information, it can be seen that availability plays a major role. As an example, in the case where a traveler is forced to accept a more expensive ticket as all cheap fares have sold out, an absence of information on availabilities will, from the modellers' perspective, suggest cost-prone choice behavior. Here, the use of SP data can have certain advantages, since it allows the explicit specification of availability and the attributes of unchosen alternatives.

In addition to the work of Adler et al. (2006), there have been a few other studies using

SP data. One example of an application using SP data is given by Bradley (1998), who uses binary logit models in the analysis of the choice of departure airport and route, with data collected from passengers at Schiphol (Amsterdam), Brussels, and Eindhoven airports. The most significant impact on choice behaviour is found to be the air fare, where a log-transform was used, and where differences exist across different groups of travelers. Proussaloglou and Koppelman (1999) use a telephone survey resembling a booking process, for passengers from whom information about actual trips had previously been collected. Respondents then made a choice of carrier, flight and fare class for their specific route. The results show negative impacts of fare, especially for leisure travelers, as well as for schedule delay, with positive impacts for frequent flier programmes. Similarly, increased market presence of the carrier, and quality of service had positive effects. Algers and Beser (2001) discuss the modeling of the choice of flight and booking class. They acknowledged the limitations of RP data in this context, but also stress those issues with SP bias need to be borne in mind. The limitations of RP is that it can be difficult to obtain sufficient variations in the RP data to examine all variables of interest. There are often strong correlations between explanatory variables of interest, this make it difficult to estimate model parameters reflecting the proper trade-off ratios (Algers and Beser, 2001). As such, they proposed to use both RP and SP data in the analysis, with the RP data being used to correct the scale of the utility function obtained with the SP data.

Finally, Lijesen (2006) made use of SP data in conjunction with MMNL models to look at the valuations of schedule delay and discussed the impact of these findings in terms of recommendations for airlines' optimal flight schedules. As a review on the methodology of generalized random utility models including the latent class models; more recently Walker and Li (2007) studied lifestyle preferences to form latent classes of individuals that have different residential location choice. They estimated the class membership and choice models simultaneously and they provided future directions in including psychometric indicators in the latent class framework as additional measurements for the class membership. Wen and Lai (2010) explored a latent market segmentation for international airline passengers' preferences using stated preference data and latent class model.

1.3 Statement of the problem

In order for the Namibian airline industry to progress, they need to know the stated preferences of the passengers on the type of carrier(s) they would prefer in order to meet their travelling demands. In addition, the industry should know the type of passengers available and their preferences. However, right now in Namibia there exists only a full service carrier, which is a national carrier, and charter services. High prices of FSC and charter services give less opportunity to middle and low income group to travel by air. Affordable prices through an introduction of LCC may increase the revenue base of the airline industry, thus ensuring sustainability. Consequently, this study intends to explore the passengers' preferences to inform appropriate airline business models.

1.4 Research objectives

The main objective of the study is to model the stated preference of air travellers and its determinants in order to inform the right industry for passengers in Namibia.

The specific objectives are:

(a) To model the stated preference of air travelers in Namibia.

(b) To assess Namibian air travelers' stated preferences based on their profiles.

(c) To compare different models used in analyzing stated preference.

(d) To propose the appropriate airline industry in Namibia.

1.5 Significance of the study

Stated preference or discrete choice models have been used to determine likely response to economic goods, thus may propose most probable form of carriers that are applicable to Namibian airline industry, perhaps advise Air Namibia on an ideal form that will maximize profits and divert from bankruptcy. The research will benefit the airlines with an alternate arrangement from bankruptcy to profit maximization by means of sound knowledge about passenger preference. This creates a justified choice of the right airline industry to invest in.

1.6 Research ethics

Informed consent was fully implemented. Before a questionnaire was given the any passenger, they were briefed on the nature of the study and given the choice of either participating or not participating. They were further informed that, if they agree to participate, they have the right to withdraw from the survey anytime because any participation in a survey was strictly voluntary. Furthermore, responses from this survey were kept confidential and was strictly used for the purpose of this study. Arbitrary code number were used to label questionnaires for identification rather than using the participants' names to ensure anonymity.

1.7 Organization of the thesis

The report will address an introduction in Chapter 1 as above then data background and description in Chapter 2. The data is analyzed in two methods, namely Binary and Latent, therefore Chapter 3 and Chapter 4 concentrate on data analysis using the two methods respectively, which starts with the introduction of the method then the method modelling and estimation, then the application and finally the discussions. Conclusion and future research direction comes in Chapter 5. Finally the Appendix includes SPSS and R codes and the sample questionnaire

Chapter 2

Study Design, Data and Descriptives

2.1 Study Design

This study followed a quantitative cross-sectional study design, in which a random sample was drawn and interviewed through a face-to-face questionnaire. A cross-sectional study is an observational one, this means that researchers record information about their subjects without manipulating the study environment. Further, a cross-sectional study offers just a snapshot of existing situation, which if there was a follow up these preferences may change. It is a quantitative research because we aimed at determining the relationship between independent variables and dependent variables in a population.

2.2 Target Population

The target population was all air passengers departing and arriving in Namibia, although only the departing passengers were interviewed. However, these departing passengers were at a point arriving passengers. According to the Namibia Airports Company (NAC) annual report (Namibia Airports Company, 2013), on average there are $33,571$ passengers traffic per month out of Hosea Kutako international airport (HKIA) and $3,723$ out of Eros airport (EA). This brings the target population to $37,294$ passengers. HKIA is a "hub and spoken" for Air Namibia, where passengers transit to different destinations via South Africa, Zambia, Zimbabwe, Ghana and Frankfurt [Germany]. A Hub and Spoke network is a route network where an airline not only plan on transporting passengers between two points, but also to connect passengers between two distant cities via its hub. Additional to the national airline (Air Namibia), South African Airways, British Airways, Linhas Aereas De Angola (TAAG Angola Airlines) and South Africa Express operate from HKIA.

2.3 Sample size

A simple random sampling method was used to select 285 passengers from two Windhoek airports. The sample size of the study was calculated using

$$n = \frac{N}{1 + \frac{N(L/100)^2}{Z_{\alpha}^2 P(1-P)}} \tag{2.1}$$

where, n=sample size, N= population size L= reliability of the estimate at the given confidence interval. Given the population of the study at the two airports, $N = 37,294$ and assuming that the desired reliability is not more than 5% at 95% confidence level in all questions that seek to estimate proportions, with sample proportion of $P = 0.25$ (P = the proportion likely to use LCC), $n = 285$ passengers were interviewed, by assuming that the observed proportion with this sample size has a normal distribution.

2.4 Pilot study

Data collection process started off with a pilot survey in October 2013 and 50 passengers were interviewed at HKIA departure lounge. The passengers were approached as they were entering the departure lounge from the police screening point and they were asked if they could fill in a questionnaire for this study. The questionnaires were only given to the passengers that agreed to take part in the survey. The pilot survey was only carried out at HKIA because it is the bigger and busy airport comparing to EA and the researcher assumed that HKIA would need advanced logistics unlike EA. The pilot survey was carried out to test the questionnaire and the approach so that we could improve the production of the desired information. The pilot survey also provided an opportunity to identify unanticipated responses and situations therefore this led to adjusting the questions response categories and the survey script where necessary. The passengers' response rate was 90%.

2.5 Data collection

Data were collected through a face to face interview, in which a questionnaire (see Appendix) was administered at HKIA and EA. Data were collected from flying out (departing) passengers from the two airports. The interviewed passengers were those that were sitting in the departure lounge of the two airports. Passengers were approached while they were waiting to board their flights. The passengers were approached as they were entering the departure lounge from the police screening point and they were asked if they could fill in a questionnaire for this study. The questionnaires were only given to the passengers that agreed to take part in the survey. The interviewed passengers were flying from HKIA and EA to various destinations with either by Air Namibia, South African Airways, British Airways, Linhas Aereas De Angola (TAAG) or South Africa Express. Passengers that were interviewed were randomly selected, proportional to size from the two airports-HKIA and Eros airport, in the ratio of 9:1 respectively.

Air passengers' surveys in departure lounges were conducted, because they are more willing to be interviewed or complete a survey form when they are no longer anxious about whether they will make their flight and they are relaxed, thus being less inconvenienced.

The main survey data collection took place between November 2013 and February 2014. The main survey started off at the small airport, Eros airport, that accommodates mostly domestic scheduled flights and small airplane charters to Ondangwa, Rundu, Katima Mulilo found in the Northern and North-eastern regions of Namibia. Some charters go to the Namibian coastal area and Namibian and neighborhood game reserves destinations. Interviews at Eros Airport allowed more domestic passengers to part take in the research who subsequently were passengers of interest in this research. Succeeding, HKIA accommodates domestic, regional and international passengers to local destinations like Walvis Bay, !Nami#nus (former Luderitz) and Oranjemund and to neighboring countries like the Southern African Development Community (SADC) countries, West and East Africa, Europe and beyond.

2.6 Variables

The outcome variable that was considered was the passenger stated preference between LCC and FSC for their different travel demands. The passengers' level of education, monthly income and sources of income were the key socio-economic factors used to investigate how these variables affect the stated preferences. These variables were used to define the passengers' profiles. The reasons why passengers travel most was also considered. See questionnaire in Appendix.

2.7 Descriptive statistics for the variables

Of the 285 passengers interviewed, 41% $(n = 117)$ were females and 59% $(n = 168)$ were males. Majority 59% $(n = 169)$ of the interviewees had been married and 41% $(n = 116)$ indicated that they were single. Most of the passengers interviewed were employed 92% $(n = 263)$, pensioners 1% $(n = 4)$ and dependents 7% $(n = 18)$. On the self-defined economic status, more than half of the interviewed group indicated that they were neither well-off nor poor but they were just above average. On monthly income they specified that only around 6% ($n = 18$) of the respondents earned 5000 Namibia dollars or less and the rest of the group earned better than 5000 Namibia dollars with 27% ($n = 77$) earning 20 000 to 30 000 Namibia dollars monthly. At least 60% ($n = 170$) interviewee specified that they have Tertiary education, 38% ($n = 109$) with Higher education and 2% with lower education level (Table 2.1).

Pearson chi-square indicated that there was an association between education level and ethnic groups ($p = 0.017$). An association existed too between education level and monthly income ($p < 0.05$). Also pearson chi-square test further indicated that there was an association between source of income and gender ($p = 0.041$). See Table 2.1.

Passengers travel for two main reason; leisure and business thus only 18% ($n = 51$) were travelling for leisure and the rest of the interviewees were travelling for business. According to Fig 2.1, 61% of the respondents' tickets were paid by companies were for Namibians and about 39% were for non-Namibians. At least 64% of tickets were paid for by companies and 34% ($n = 102$) were paid either by the respondents themselves or by someone else i.e. partner, friends and relatives colleagues. Among those that paid for their own tickets (as demarcated by nationality in Fig 2.1) there were the rebate respondents (1% $n = 4$). Furthermore, more than half of the participants indicated that they find air ticket prices not affordable 52% ($n = 149$) and the rest felt that they were affordable 47% ($n = 136$). Among the group there were 1.4% ($n = 4$) passengers who were flying with reward tickets. Fig 2.1 indicated that company tickets are used more by Namibians than non- Namibians.

Table 2.1: Crosstabulation for Level of Education and Source of Income by Gender

—			GENDER RESPONDENTS		TOTAL
VARIABLE	**CATEGORY**		**0 FEMALE**	**1 MALE**	
EDUCATION LEVEL	1 LOWER EDUCATION	COUNT	2	4	6
		%	1.7%	2.4%	2.1%
		Std. Residual	-0.3	0.3	
	2 HIGHER EDUCATION	COUNT	48	61	109
		%	40.7%	36.5%	38.2%
		Std. Residual	0.4	-0.4	
	3 TERTIARY	COUNT	68	102	170
		%	57.6%	61.1%	59.6%
		Std. Residual	-0.3	0.2	
TOTAL		COUNT	118	167	285
		%	100%	100%	100%
SOURCE OF INCOME	0 DEPENDENT	COUNT	13	5	18
		%	11.0%	3.0%	6.3%
		Std. Residual	2.0%	-1.7%	
	1 EMPLOYED	COUNT	84.00	136.00	220.00
		%	71.2%	81.4%	77.2%
		Std. Residual	-0.7	0.6	
	2 SELF EMPLOYED	COUNT	19	24	43
		%	16.1%	14.4%	15.1%
		Std. Residual	0.3	-0.2	
	3 PENSION	COUNT	2	2	4
		%	1.7%	1.2%	1.4%
		Std. Residual	0.3	-0.2	
TOTAL		COUNT	118	167	285
		%	100%	100%	100%

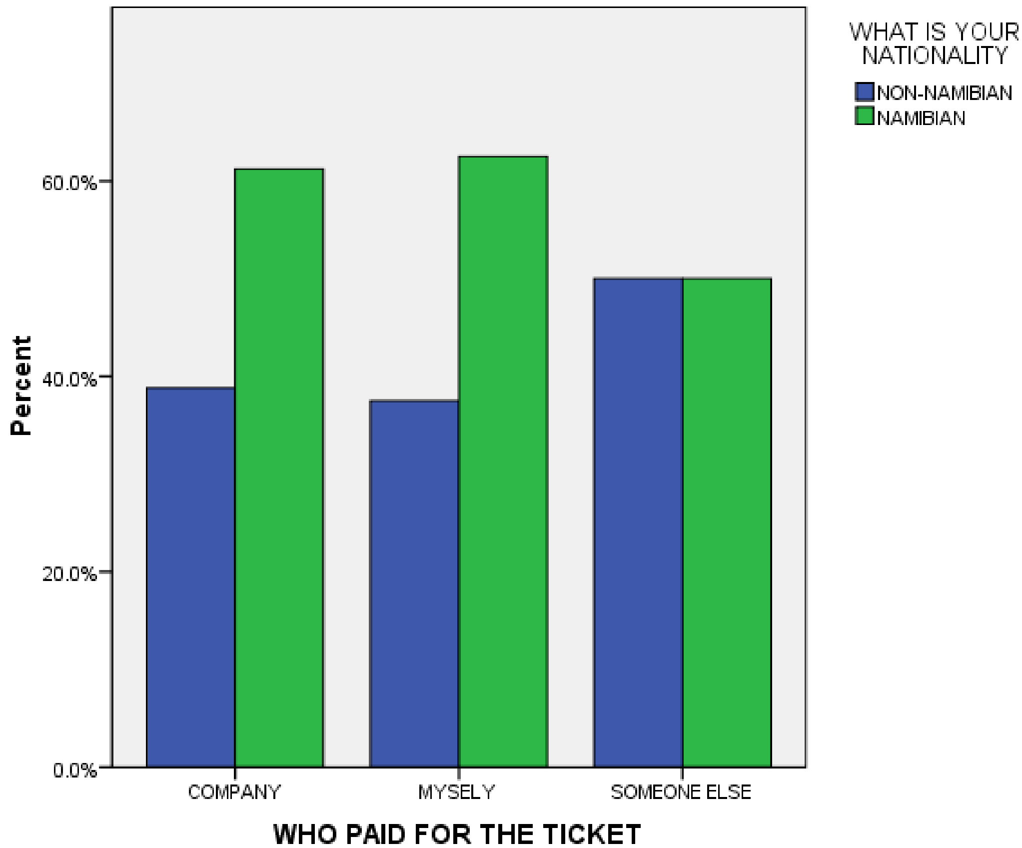

Fig. 2.1: Party that paid for the flight ticket plotted against Nationality

Data summaries further revealed that the use of technology, about 218 (77%) respondents itemized that they checked in at the airport and about 15% $(n = 43)$ checked-in online. The rest did it telephonically. Further, 63% $(n = 182)$ made their reservations through travel agencies, 11% n$(n = 32)$ through airline call centers, 24% $(n = 67)$ online and 2% through their tour operators. In the contrast, 83% $(n = 237)$ of the participants found online services convenient and 2 participants had never used online services before. Not all respondents had an idea what LCCs are. At least 51% $(n = 146)$ indicated that they do not know what an

LCC is and they could not differentiate it with any other type of carrier. In addition to this, about 62% $(n = 117)$ never flew LCC before the date of the interview. After the passengers where explained to what LCC is and how it operates, around 91% $(n = 259)$ stated that, if they had that option, in general they would prefer to fly LCC and only 9% $(n = 26)$ stated that they would prefer to fly FSC.

About 32% $(n = 92)$ indicated that they choose to fly a specific airline because of the airline convenience, while around 30% $(n = 84)$ said they choose to fly specific airlines because it was the only option they had. On the other hand about 66 passengers (23%) specified that they fly specific airlines because of cheap fares whereas 15% $(n = 15)$ said that they fly specific airlines because of loyalty due to either company policy or other reasons. However, there was an association between airline specific and ethnic groups $(p < 0.05)$. There is an indication that female turn to prefer airlines with cheap fares and they are more loyal comparing to males (Figure 2.2) In fact, only 17% $(n = 48)$ had flown less than two times on the day of the interview.

2.8 Conclusion

We collected sufficient data to assist us achieve our study objectives and now we use these variables to study in detail the air travellers' choices and its determinants in Namibia. These are covered in Chapters 3 & 4.

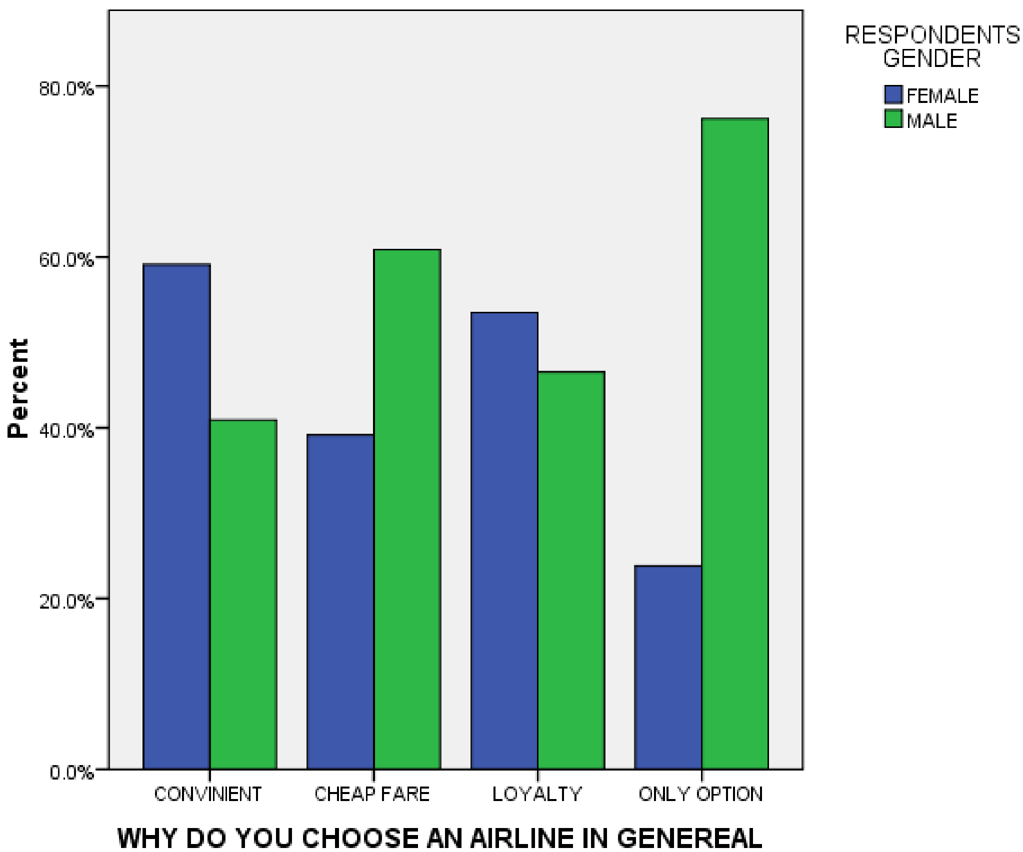

Fig. 2.2: Reasons behind choosing a specific airline

Chapter 3

Airline carrier choices and preferences among air travelers in Namibia

3.1 Introduction and Background

Following the procedures of Russell and James (2013), discrete choice models, such as the binary logit and multinomial logit, are used to predict the probability a decision-maker (often an individual, group of individuals or corporates) will choose one alternative among a finite set of mutually exclusive and collectively exhaustive alternatives.

Currently, there is a growing interest in applying discrete choice models in the airline industry. This interest is driven by the desire to more accurately represent why an individual makes a particular choice and how the individual makes trade-offs among the characteristics of the alternatives.

Integrating discrete choice and other models grounded in behavioral theories with traditional revenue management, scheduling, and other applications is also being driven by several factors, including the increased market penetration of low cost carriers, wide-spread use of the internet, elimination and/or substantial reduction in travel agency commissions, and introduction of simplified fare structures by network carriers (Garrow, 2010). The presence of low cost carriers has reduced average market fares and increased the availability of low fares. Moreover, Garrow (2010) indicated that the internet has reduced individuals searching costs and made it easier for individuals to both find these fares and compare fares across multiple carriers without the assistance of a travel agent. In addition, the elimination of commissions has removed the incentive of travel agencies to concentrate sales only on those carriers offering the highest commissions.

According to Garrow (2010), the introduction of simplified fare structures by network carriers was motivated by the need to offer products competitive with those sold by low cost carriers. Often, low cost carrier products do not require Saturday night stays and have few fare-based restrictions. However, these simplified fares have been less effective in segmenting price-sensitive leisure passengers willing to purchase weeks in advance of flight departure from time-sensitive business passengers willing to pay higher prices and needing to make changes to tickets close to flight departure. All of these factors have resulted in the need to better model how passengers make purchasing decisions, and to determine their willingness to pay for different service attributes. Moreover, Garrow (2010) further detailed that unlike traditional models based solely on an airlines internal data, there is now a perceived need to incorporate existing and/or future market conditions of competitors when making pricing, revenue management, and other business decisions. Discrete choice models provide one framework for accomplishing these objectives.

This chapter presents fundamental concepts of choice theory and reviews two of the most commonly used discrete choice models: the binary logit models and probit, subsequently we use these to evaluate travellers' choices in Namibia.

3.2 Literature Review

A wide range of studies have investigated air travel choice behavior. Mamdoohi et al. (2013) used binary logit to model the origin airport choice of resident and non-resident travelers from the city of Tehran. The results showed that the difference in the two groups is affected by ”age”, ”income”, ”travel destination”, ”trip purpose” and “marital status”. Furthermore the results showed that variables “public access”, “flight frequency” and “airport tax” are more important for non-resident air travelers in choosing their origin airport. Ashford and Bencheman (1987) developed a multinomial logit model to analyze air passengers' choice in central London. This study showed that for business and inclusive tour travel, the most important variables of choice were access time to the airport and frequency to the chosen destination. For domestic and leisure trips, there were three factors: airfare, access time, and frequency of available flights, in that order of importance. Davidson and Ryley (2010) performed a binary logit modelling in airport choice in which the air fare was the most meaningful variable whereas the travel time was the second one. Hess and Polak (2005a) extended it to a mixed multinomial logit model to analysis of the choice of airport, airline and access-mode for travelers living in the San Francisco bay area. Results indicated that the most important variables affecting traveler's choices were in-vehicle access time, access-cost and flight frequency.

In a related study, a binary logit was used for airport selection in which the most meaningful variables were airfare, access time and frequent flyer benefits (Hess et al., 2007). Another study by Pels et al. (2009) developed a nested logit model to investigate low-cost airline and airport competition in greater London. Pels et al., (2009) analyzed most important factors affecting air travellers' choices such as airfare, surface-access costs and frequency. Stefano (2012) used discrete choice random utility models (multinomial logit, mixed multinomial logit and cross-nested logit models) to investigate and model airport choice behaviour in a multi-airport region in Campania, southern Italy. He found that access time, airfare, age, experience and income were the most significant variables.

When passengers choose a carrier, they may base their decision on a combination of factors, including the airline's market presence, schedule convenience, low fares, on time performance, reliability and the availability of frequent flyer programs (Proussaloglou and Koppelman, 1999). Hess et al. (2007) studied the airport and airline choice behavior with the use of stated preference survey data. The study analyzed factors affecting passenger choice behavior, including air fare, access time, flight time and airline and airport allegiance using multinomial logit model. Pels et al. (2003) used nested logit model and found that passengers are sensitive to fare, frequency, airport access time and airport access cost. Pels et al. (2009) further studied the competition between full service and low cost airlines by analyzing the demand structure. They estimated not only the competition for passengers occurring between airports and airlines, but also the own-and cross-price elasticities based on a nested logit model.

There are significant differences in choice behavior between business travelers and non-business travelers (Chang and Sun, 2012). Most business travelers have strict requirements regarding travel time and will seldom strive for lower prices because they are restricted by time inflexibility. On the contrary, leisure travelers will choose the lower price among two acceptable flight choices (Xiao et al., 2008).

3.3 Modelling Travelers' Choices and Preferences

3.3.1 Binary logit and probit models

A dichotomous-choice response question is examined, "Why does a traveler choose a particular airline (LCC = 1) over its alternative (FSC = 0) in his/her travel decision making?" A log-odds model is adopted and estimated using logit analysis of the form :

$$\log[P/(1-P)] = \beta_0 + \beta_1 X_1 + ... + \beta_p X_p + \epsilon \tag{3.1}$$

where, P is the probability of the respondent to travel by a particular carrier (i.e. LCC); $X_i, i = 1, 2, 3, ..., p$ are explanatory variable hypothesized to influence the probability as defined in Table 3.1; while β are coefficients for the explanatory variables; ϵ is stochastic disturbance term; and, $P/(1-P)$ is the ratio of the probability that the respondent travels by LCC to the probability that he/she travels by FSC. It can also be considered as the odds of the respondent to travel by LCC over FSC (Ong and Tan, 2010). An alternative to model (3.1) is to consider a probit model that assumes the function $F(\cdot)$ follows a normal (cumulative) distribution by Greene and Hensher (2010),

$$F(x) = \Phi(c) = \int_{-\infty}^{x} \phi(z)dz \tag{3.2}$$

where $\phi(z)$ is the normal density function,

$$\phi(z) = \frac{\exp(-\frac{z^2}{2})}{\sqrt{2\pi}} \tag{3.3}$$

.

A probit applies when ϵ is assumed to follow a cumulative standard normal distribution while a logit is obtained if cumulative logistic model is used (Ong and Tan, 2010).

3.3.2 Estimation: Maximum Likelihood Estimation of Binary Response Models

We adapted Greene and Hensher (2003)'s approach on maximum likelihood estimation. Estimation and inference for probit and logit models for binary choices are usually based on maximum likelihood estimation. However other approaches like the Bayesian are possible (Cheeseman and Stutz, 1995). Because the dependent variable is discrete, the likelihood function cannot be defined as a joint density function as with a continuously distributed dependent variables.

Each observation is a draw from a Bernoulli distribution (binomial with one trial). The model with success probability $F(\gamma' x_i)$ and independent observations leads to the joint probability, or likelihood function,

$$Prob(Y_1 = y_1, Y_2 = y_2, ..., Y_n = y_n | x_1, x_2, ..., x_n) = \prod_{y_i=0} [1 - F(\gamma' x_i)] \times \prod_{y_i=1} F(\gamma' x_i). \quad (3.4)$$

Let X denote the sample of n observations, where the ith row of X is the ith observation on x_i (transposed, since x_i is a column) and let y denote the column vector that is the n observations on y_i. Then, the likelihood function for the parameters can be written

$$L(\gamma | X, y) = \prod_{i=1}^{n} [1 - F(\gamma' x_i)]^{1-y_i} [F(\gamma' x_i)]^{y_i}. \quad (3.5)$$

Taking logs, we obtain the log likelihood function,

$$\ln L(\gamma | X, y) = \sum_{i=1}^{n} (1 - y_i) \ln[1 - F(\gamma' x_i)] + y_i \ln F(\gamma' x_i) \quad (3.6)$$

We are limiting our attention to the normal and logistic, symmetric distributions. This permits a useful simplification. Let

$$q_i = 2y_i - 1. \quad (3.7)$$

Thus, $q_i = -1$ when y_i equals zero and $q_i = +1$ when y_i equals one. Because the symmetric distributions have the property that

$F(t) = 1 - F(-t)$,

we can combine the preceding into

$$\ln L(\gamma | X, y) = \sum_{i=1}^{n} \ln F[q_i(\gamma' x_i)] \quad (3.8)$$

The maximum likelihood estimator (MLE) of γ is the vector of values that maximizes this function. The MLE is the solution to the likelihood equations,

$$\frac{\partial \ln L(\gamma|X,y)}{\partial\gamma} = \sum_{i=1}^{n}\left\{q_i \frac{f[q_i(\gamma' x_i)]}{F[q_i(\gamma' x_i)]}\right\} x_i = 0, \tag{3.9}$$

where $f(\cdot)$ is the density, $dF(.)/d(\gamma' x_i)$. The likelihood equations will be nonlinear and require an iterative solution. For the logit model, the likelihood equations can be reduced to

$$\frac{\partial \ln L(\gamma|X,y)}{\partial\gamma} = \sum_{i=1}^{n}[y_i - \Lambda(\gamma' x_i)]x_i = 0. \tag{3.10}$$

If x_i contains a constant term, then, by multiplying the likelihood equation by $1/n$, the first-order condition with respect to the constant term implies

$$\frac{1}{n}\sum_{i=1}^{n}[y_i - \Lambda(\widehat{\gamma}' x_i)] = 0, \tag{3.11}$$

where $\widehat{\gamma}$ is the MLE of γ. That is, the average of the predicted probabilities will equal the proportion of ones in the sample, $P_1 = (\frac{1}{n})\sum_i y_i$. Although the same result has not been shown to hold exactly (theoretically) for the probit model, it does appear as a striking empirical regularity there as well. The likelihood equation also bears some similarity to the least squares normal equations if we view the term $y_i - \Lambda(\gamma' x_i)$ as a residual. The first derivative of the log likelihood with respect to the constant term produces the generalized residual in many settings.

Greene and Hensher (2003) further indicated that it is common in some areas, such as transportation, to report elasticities of probabilities, rather than derivatives. Elasticity is used mainly by economists to describe the degree of responsiveness of the endogenous variable in an economic model with respect to the changes in the exogenous variable of the model. It measures the percentage change in the endogenous variable when the exogenous variable is increased or decreased by 1%. So the concept of elasticity will be useful to measure the sensitivity of the price of a products corresponding to market movements. These are straightforward to compute as

$$\epsilon_{i,k} = \frac{\partial \ln Prob(y_i = 1|x_i)}{\partial \ln x_{i,k}} = \frac{\partial Prob(y_i = 1|x_i)}{\partial x_{i,k}} \frac{x_{i,k}}{Prob(y_i = 1|x_i)}. \tag{3.12}$$

The elasticities are simple to obtain from the estimated partial effects. However, since it is a ratio of percentage changes, the elasticity is not likely to be useful for dummy variables such as marital status, or for discrete variables such as age and education level. Like a partial effect, an elasticity for a dummy variable or an integer valued variable will not necessarily produce a reasonable result. The computation for a dummy variable or an integer variable would be a semi-elasticity, $[\%\Delta Prob]/\Delta x$, where Δx would equal one. Whether a percentage change in an integer valued x would make sense would depend on the context (Greene and Hensher, 2003).

3.4 Application

Primary data from 285 departing passengers at the two Windhoek airports were analyzed to model four binary logit and probit models. The data set include aspects that affect choice of carrier; behavioural aspects and socio-demographic factors. The dependent variable is defined as passenger's stated preference for k flights = 1 if LCC otherwise 0 if FSC, where

k is either domestic, regional,international or general flights. The following variables were used in the regression part of the model,

$$x_i = (constant, gender, income, educationlevel, maritalstatus, age, nationality).$$

The predictor variables were identified in line with the objectives of this study as we seek answers to the objectives of the study. These variables will assist us identify what determinants inform the stated preferences based on passengers profiles and when this is assessed, the Namibian airline industry can be informed accordingly given the SP knowledge of their passengers.

In the original data set, income is divided into three parts as INCOM1, INCOM2, INCOM3 representing low, mid and high income respectively. Education level is TERTIARY which is a binary variable, the latter indicating whether or not the respondent has attended tertiary level.

Descriptive statistics for the data used in the analysis are shown in Table 3.1 and 3.2. Estimates of the parameters of the logit and probit models are shown in Table 3.3, 3.4, 3.5 and 3.6. The estimates for the two models have close p-values.

The assumptions of Binary response model are that the outcome must be discrete, otherwise explained as, the dependent variable should be dichotomous in nature (e.g. LCC vs. FSC). There should be no outliers in the data, which can be assessed by converting the continuous predictors to standardized, or z scores, and remove values below -3.29 or greater than 3.29. There should be no high intercorrelations (multicollinearity) among the predictors. This can be assessed by a correlation matrix among the predictors. Tabachnick and Fidell (2012) suggested that as long as correlation coefficients among independent variables are less than 0.90 the assumption is met. Hence the binary logit assumptions are met and analysis proceeded.

Table 3.1: Description and summary statistics of variables in the statistical model fitted

VARIABLE	DESCRIPTION	MEAN	STD.DEV
WHYTHEAIRLINEGEN	1= THEY CHOOSE AN AIRLINE DEPENDING ON THE FARE 0=OTHERWISE	1.51	1.143
FLYMOSTLCCFSC	1= LCC 0=FSC	0.91	0.288
WHYAIRLINESPC	1= FARE 0=OTHERWISE	2.57	1.484
TICKETPAYER	1= MYSELF 0=OTHERWISE	0.41	0.584
RESERVATIONSPOINT	1= RESERVATION MADE ONLINE 0=OTHERWISE	2.18	1.138
ONLINESVCS	1= ONLINE SERVICES IS CONVINIENT 0 OTHERWISE	0.32	0.727
LONGHAULS	1= PREFER LCC ON LONGHAULS 0= PREFER FSC ON LONGHAULS	0.31	0.463
DOMESTIC	1= PREFER LCC ON DOMESTIC 0= PREFER FSC ON DOMESTIC	0.81	0.395
REGIONAL	1= PREFER LCC ON REGIONAL 0= PREFER FSC ON REGIONAL	0.66	0.475
GENERALFLIGHT	1= PREFER LCC IN GENERAL 0= PREFER FSC IN GENERAL	0.6	0.491
NATIONALITY	1= NAMIBIAN 0= NON-NAMIBIAN	0.61	0.488
GOVERNMENT	1= GOVERNMENT EMPLOYEE 0= OTHERWISE	0.13	0.333
TERTIARYEDU	1= TERTIARY EDUCATED 0= OTHERWISE	0.6	0.491
INCOM1	1= 0 -9999 (LOW INCOME) 0= OTHERWISE	0.16	0.369
INCOM2	1= 10 000 -29 999 (MID INCOME) 0= OTHERWISE	0.51	0.501
INCOM3	1= 30 000 - 40 000+ (HIGH INCOME) 0= OTHERWISE	0.31	0.461
MARITAL_STATUS	1= SINGLE 0= EVERMARRIED	0.41	0.492
GENDER	1= MALE 0= FEMALE	0.59	0.493
YOUTH	1= 15-34 YOUTH 0= OTHERWISE	0.38	0.485
ADULT	1= 35-54 ADULT 0= OTHERWISE	0.51	0.501
SENIORCITIZV	1= SENIOR CITIZEN 0= OTHERWISE	0.1	0.303
FAREMATTERS	1= CHOICE BASED ON FARE 0= OTHERWISE	0.36	0.48
ONLINECONVINIENT	1= CONVINIENT 0= OTHERWISE	0.18	0.384
FLYREASON	1= BUSINESS 0= OTHERWISE	0.89	0.316

The results are presented according to regions of destinations, which are domestic, regional and international plus the passengers general flying preference. All analysis were

Table 3.2: Frequency table for passengers SP for all regions of destinations and in general.

		DOMESTIC		REGIONAL		INTERNATIONAL		GENERAL	
VARIABLE†	CATEGORY	**FSC % (n)**	**LCC % (n)**	**FSC % (n)**	**LCC % (n)**	**FSC % (n)**	**LCC % (n)**	**FSC % (n)**	**LCC % (n)**
GENDER	FEMALE	15 (18)	85 (100)	26 (31)	74 (87)	61 (72)	39 (46)	35 (41)	65 (77)
	MALE	22 (37)	79 (130)	40 (66)	61 (101)	75 (125)	25 (42)	44 (73)	56 (94)
NATIONALITY	NAMIBIAN	20 (34)	80 (140)	29 (50)	31 (124)	66 (114)	34 (60)	35 (61)	65 (113)
	NON-NAMIBIAN	19 (21)	81 (90)	42 (47)	58 (64)	75 (83)	25 (28)	48 (53)	52 (58)
MARITAL STATUS	EVER MARRIED	18 (30)	82 (139)	34 (58)	66 (111)	68 (115)	32 (54)	36 (60)	64 (109)
	SINGLE	22 (25)	78 (91)	34 (39)	66 (77)	71 (82)	29 (29)	47 (54)	53 (62)
LEVEL OF EDUCATION	LOWER	17 (1)	83 (5)	17 (1)	83 (5)	50 (3)	50 (3)	17 (1)	83 (5)
	HIGHER	25 (27)	75 (82)	29 (32)	71 (77)	66 (72)	34 (37)	33 (36)	67 (73)
	TERTIARY	16 (27)	84 (143)	38 (64)	62 (106)	72 (122)	28 (48)	45 (77)	54 (93)
AGE	0-34 (YOUTHS)	16 (23)	84 (83)	25 (32)	75 (74)	86 (80)	14 (26)	39 (51)	61 (55)
	35-54 (ADULTS)	28 (27)	72 (123)	35 (52)	65 (98)	65 (97)	35 (53)	32 (49)	68 (101)
	55+ (SENIORCITIZN)	17 (5)	83 (24)	45 (13)	55 (16)	75 (52)	25 (17)	48 (14)	52 (15)

† Variable names have been explained in Table 3.1

carried out using SPSS (17) and R (3.1.0) software's.

3.4.1 Passenger Stated Preferences for Domestic flights

Summaries on frequencies of passenger stated preferences for all destination regions are provided in Table 3.2. On average, about 81% of respondents stated that they prefer LCC on domestic routes.

Table 3.3 shows the estimates of the parameters of the probit and logit models for domestic preferences. The results indicated that within domestic flights, choice of LCC had significant association with ticket fares, flying reason and tertiary education level. More specific, ticket fares had a negative significant association while flying reason and tertiary

Table 3.3: Passenger Stated Preferences for Domestic Flights

	LOGIT				PROBIT			
			CI (95%)				CI (95%)	
VARIABLE	† **COEF (B)**	‡ **SIG**	**LOWER**	**UPPER**	**COEF (B)**	‡ **SIG**	**LOWER**	**UPPER**
CONSTANT	0.7187	0.010	(-2.198	3.849)	0.479	0.586	(-1.252	2.259)
FARESMATTERS	-0.914	0.010 (*)	(-1.618	-0.227)	-0.491	0.01316 (*)	(-0.881	-0.105)
FLYREASON	1.459	0.010 (*)	(0.418	2.651)	0.853	0.0059 (*)	(0.269	1.486)
TERTIARYEDU	0.939	0.010 (*)	(0.238	1.657)	0.527	0.0094 (*)	(0.134	0.925)
YOUTH	1.140	0.278	(-1.103	3.188)	0.661	0.293	(-0.652	1.916)
ADULT	1.427	0.158	(-0.744	3.413)	0.800	0.188	(-0.462	2.011)
SENIORCITIZV	1.768	0.119	(-0.586	4.013)	0.968	0.149	(-0.396	2.304)
MARITAL_STATUS	-0.145	0.714	(-0.921	0.633)	-0.098	0.661	(-0.541	0.345)
GENDER	-0.179	0.635	(-0.931	0.558)	-0.118	0.577	(-0.532	0.292)
GOVERNMENT	0.117	0.841	(-0.980	1.326)	0.018	0.956	(-0.588	0.653)
NATIONALITY	-0.195	0.615	(-0.964	0.560)	-0.097	0.658	-0.528	0.330
ONLINECONVINIENT	-0.499	0.402	(-1.810	0.578)	-0.275	0.392	(-0.941	0.330)
INCOM1	-1.331	0.188	(-3.524	0.517)	-0.823	0.152	(-2.061	0.292)
INCOM2	0.583	0.533	(-1.453	2.297)	0.283	0.589	(-0.852	1.306)
INCOM3	-0.674	0.475	(-2.717	1.052)	-0.408	0.443	(-1.553	0.633)

† Variable names have been explained in Table 3.1

‡ COEF (B)=Coefficient; SIG.=p-value; (*) model significance at 5%;

education level had a positive significant association. Never the less it is worth mentioning that age (YOUTH, ADULT and SENIORCITIZV), being a government employee and mid income earners were also positively associated with choice of LCC so these passengers are more likely to prefer LCC than passengers who were single, males, Namibians and low and high income earners as they were negatively associated with the choice of LCC on domestic flights.

Using a logit the same is confirmed by using probit because they have the same indica-

Table 3.4: Passenger Stated Preferences for Regional Flights

	LOGIT				PROBIT			
			CI (95%)				CI (95%)	
VARIABLE	† **COEF (B)**	‡ **SIG**	**LOWER**	**UPPER**	**COEF (B)**	‡ **SIG**	**LOWER**	**UPPER**
CONSTANT	1.50167	0.297	(-1.281	4.458)	0.883	0.299	(-0.811	2.635)
FARESMATTERS	-0.34493	0.229	(-0.909	0.217)	-0.203	0.241	(-0.542	0.136)
FLYREASON	0.49196	0.243	(-0.315	1.347)	0.287	0.248	(-0.198	0.787)
TERTIARYEDU	-0.02272	0.939	(-0.606	0.558)	-0.041	0.819	(-0.390	0.307)
YOUTH	0.41306	0.698	(-1.844	2.522)	0.242	0.706	(-1.126	1.544)
ADULT	0.4135	0.690	(-1.789	2.475)	0.245	0.695	(-1.083	1.515)
SENIORCITIZV	0.13966	0.899	(-2.171	2.33)	0.080	0.905	(-1.321	1.431)
MARITAL_STATUS	0.09775	0.760	-0.53	0.726	0.040	0.836	-0.342	0.422
GENDER	-0.17324	0.574	(-0.78	0.431)	-0.076	0.679	(-0.436	0.285)
GOVERNMENT	1.62213	0.014 (*)	(0.454	3.131)	0.892	0.010 (*)	(0.251	1.618)
NATIONALITY	0.21228	0.499	(-0.407	0.826)	0.155	0.417	(-0.214	0.522)
ONLINECONVINIENT	-1.0337	0.043 (*)	(-2.119	-0.086)	-0.598	0.041 (*)	(-1.187	-0.045)
INCOM1	-0.70112	0.446	(-2.683	1.011)	-0.436	0.417	(-1.545	0.600)
INCOM2	0.06412	0.939	(-1.765	1.612)	0.049	0.919	(-0.957	0.981)
INCOM3	-0.98525	0.240	(-2.814	0.574)	-0.601	0.219	(-1.608	0.343)

†Variable names have been explained in Table 3.1

‡COEF (B)=Coefficient; SIG.=p-value; (*) model significance at 5%;

tions of significance and direction of associations. This result is consistent with the findings of O'Connell and Williams (2005) and Ong and Tan (2010) whereby fare is the principle reason for carrier selection among low-cost airline passengers. On the other hand, online services were not considered by passengers when choosing their domestic carrier preferences.

3.4.2 Passenger Stated Preferences for Regional flights

In this section we examined the stated preferences for passengers on regional fleet. Passengers stated different preferences for different fleets. On average, among the interviewed passengers, 66% indicated that their stated preference on regional fleet is LCC and only 34% stated to prefer FSC (Table 3.2).

The estimates of the parameters of the logit and probit analysis for regional flights are shown in Table 3.4. The results presented that, within regional flights, being a government employee and the use of online services, were significantly associated with the choice of LCC. Whereby, the use of online services had a negative association and being a government employee had a positive association. Moreover, apart from the use of online services, ticket fares, tertiary education level, males and low and high income earners were less likely to prefer LCC on regional flights compared to business travellers, Namibians, mid income earners, government employees, age and single passengers who had a positive association thus they were more likely to prefer LCC. These results ties in with those of Hess et al, (2007) that showed that many that fly LCC use ICT booking channels.

3.4.3 Passenger Stated Preferences for International flights

On international fleet, which are usually long hauls, passengers stated preferences are quite different from those of domestic and regional fleet. Table 3.2 displays that about 69% of interviewed passenger stated that they will prefer FSC on International routes because they are quite comfortable than LCC and on a long haul one need to travel in comfort.

Table 3.5: Passenger Stated Preferences for International Flights

	LOGIT				PROBIT			
			CI (95%)				CI (95%)	
VARIABLE	† **COEF (B)**	‡ **SIG**	**LOWER**	**UPPER**	**COEF (B)**	‡ **SIG**	**LOWER**	**UPPER**
CONSTANT	-1.785	0.237	(-4.910	1.104)	-0.900	0.295	(-2.669	0.815)
FARESMATTERS	-0.580	0.069	(-1.219	0.035)	-0.368	0.046 (*)	(-0.736	-0.007)
FLYREASON	0.653	0.109	(-0.149	1.456)	0.392	0.106	(-0.077	0.862)
TERTIARYEDU	0.061	0.845	(-0.539	0.676)	0.054	0.767	(-0.302	0.415)
YOUTH	-0.555	0.593	(-2.588	1.665)	-0.299	0.633	(-1.558	1.009)
ADULT	0.065	0.949	(-1.893	2.235)	0.041	0.946	(-1.179	1.324)
SENIORCITIZV	0.000	0.927	(-2.021	2.403)	0.084	0.898	(-1.231	1.455)
MARITAL_STATUS	0.127	0.709	(-0.539	0.796)	0.084	0.673	(-0.306	0.474)
GENDER	-0.419	0.180	(-1.035	0.194)	-0.237	0.202	(-0.604	0.129)
GOVERNMENT	1.024	0.020 (*)	(0.174	1.906)	0.622	0.018 (*)	(0.112	1.137)
NATIONALITY	0.222	0.519	(-0.451	0.903)	0.144	0.474	(-0.249	0.540)
ONLINECONVINIENT	2.099	0.006 (*)	(0.805	3.968)	1.047	0.004 (*)	(0.394	1.818)
INCOM1	-0.536	0.501	(-2.373	1.081)	-0.367	0.477	(-1.390	0.635)
INCOM2	-0.803	0.301	(-2.427	0.691)	-0.501	0.279	(-1.426	0.395)
INCOM3	-1.364	0.089	(-3.027	0.188)	-0.802	0.092	(-1.755	0.122)

†Variable names have been explained in Table 3.1

‡COEF (B)=Coefficient; SIG.=p-value; (*) model significance at 5%;

According to results in Table 3.5, the LCC choice within the international flights had significant association with ticket fares (negative association), being government employee and the use of online services (both positive association). It was evident that business travellers, tertiary educated, Namibians, adults and single users, plus the use of online services were more likely to prefer LCC on international flights compared to passengers that were youths, males and high income earners as they were negatively associated with a choice of LCC on international flights. Like on regional flights, information communication technology is a very common booking channel for LCC on international flights hence the high coefficient (2.99) for the use of online services.

3.4.4 Passenger Stated Preferences for General flights

Now turning to preferences flights in general, results show that more than half (60%) of the interviewed group stated that they prefer LCC (Table 3.2). Table 3.6 shows the results of the logit analysis for general flights. Results in Table 3.6 show trip purpose, fares and nationality are significantly related to airline choice.

Along with ticket fares, tertiary education, marital status, the use of online services and low income bracket were less associated with preferring LCC for flights in general. While business travellers, Namibians, mid income earners and adults were more likely to choose LCC for their flights in general.

3.5 Conclusion

This chapter aimed at investigating the likelihood of passengers to choose between two air carriers with dissimilar operating structures: low cost and full service carrier. The findings provide additional support to the concept that passengers' socio-demographics (occupation, education level) and behavioral choices (concerns about ticket prices, fares, online services and purpose journey) are main determinants of airline choice. The model results show that the difference in the four groups are affected by age, income, purpose of travel, fares and occupation. Furthermore, more passengers indicated that for domestic, regional and in general

Table 3.6: Passenger Stated Preferences for General Flights

	LOGIT				PROBIT			
			CI (95%)				**CI (95%)**	
VARIABLE	† **COEF (B)**	‡ **SIG**	**LOWER**	**UPPER**	**COEF (B)**	‡ **SIG**	**LOWER**	**UPPER**
CONSTANT	-0.619	0.667	(-3.501	2.241)	-0.301	0.723	(-1.992	1.378)
FARESMATTERS	-0.936	0.002 (*)	(-1.524	-0.364)	-0.527	0.003 (*)	(-0.870	-0.187)
FLYREASON	1.793	0.000 (*)	(0.889	2.796)	1.028	0.000 (*)	(0.504	1.582)
TERTIARYEDU	-0.076	0.801	(-0.666	0.516)	-0.048	0.790	(-0.399	0.304)
YOUTH	0.806	0.441	(-1.235	3.046)	0.471	0.454	(-0.772	1.764)
ADULT	1.702	0.097	(-0.294	3.915)	1.005	0.102	(-0.204	2.280)
SENIORCITIZV	1.305	0.234	(-0.822	3.629)	0.793	0.247	(-0.529	2.114)
MARITAL_STATUS	-0.201	0.531	(-0.834	0.43)	-0.113	0.559	(-0.495	0.269)
GENDER	0.316	0.311	(-0.290	0.934)	0.169	0.361	(-0.193	0.535)
GOVERNMENT	0.963	0.088	(-0.076	2.168)	0.566	0.072	(-0.027	1.200)
NATIONALITY	0.800	0.014 (*)	(0.164	1.45)	0.437	0.025 (*)	(0.063	0.813)
ONLINECONVINIENT	-0.587	0.209	(-1.544	0.302)	-0.389	0.158	(-0.951	0.152)
INCOM1	-1.027	0.278	(-3.074	0.724)	-0.557	0.306	(-1.662	0.476)
INCOM2	0.203	0.812	(-1.672	1.783)	0.125	0.799	(-0.874	1.052)
INCOM3	-0.688	0.425	(-2.572	0.907)	-0.427	0.390	(-1.434	0.516)

†Variable names have been explained in Table 3.1

‡COEF (B)=Coefficient; SIG.=p-value; (*) model significance at 5%;

flights they prefer LCC while for international flights they prefer FSC.

Chapter 4

Latent class choice model for analyzing air travel behavior in Namibia

4.1 Background

Modeling airline choices can provide an understanding of travelers' preferences and behavioral insights. The most widely used approach is the discrete choice model that allows identifying the important determinants affecting air carrier choice, and therefore, market share effects in response to changes in airline service attributes could be analyzed (Proussaloglou and Koppelman, 1999). Earlier studies employed the simple multinomial logit model to examine the selection of airlines in a single-dimension choice (Ghobrial, 1989; Alamdari and Black, 1992; Proussaloglou and Koppelman, 1995). Recent studies explored air traveler behaviors using an integrated framework which combines airline choice with other dimensions such as flight itineraries, fare classes, airports, and access modes. Hence, a variety of advanced discrete choice models has been developed and applied to air demand analysis by accommodating complex substitution patterns among alternatives and preference heterogeneity; these are the mixed logit model (Rose et al., 2005; Adler et al., 2006; Warburg et al., 2006; Espino et al., (2008), the cross-nested logit model (Hess and Polak, 2006b), and the weighted nested logit model (Coldren and Koppelman, 2005).

4.2 Latent Class Models

The standard multinomial logit model assumes the same preference structure across individuals. Such model would result in biased estimates and incorrect predictions if heterogeneous preferences exist (Walker and Li, 2007). Given a finite and fixed number of segments, the latent class model calibrates segment-specific sets of parameters, and the likelihood of the respondents belonging to a segment is a probabilistic function which depends on individual characteristics. For passenger i, the utility function of any airline j, given that it belongs to segment s, can be expressed as:

$$U_{ij|s} = \alpha_s + \beta_s^{'} X_{ij} + \epsilon_{ij|s} \tag{4.1}$$

where α_s as is a vector of unknown parameters for segment s, and within a segment, airline specific constants are included; X_{ij} is a vector of airline service attributes that are varied by airline alternatives; β_s is a vector of segment-specific parameters to be estimated; $\epsilon_{ij|s}$ captures a random error of the utility function. In the latent class model, the probability of an airline j being chosen by passenger i is given by

$$P_i(j) = \sum_{s=1}^{s} P_i(j|s) \cdot M_i(s) \tag{4.2}$$

where

$$P_i(j|s) = \frac{\exp(\alpha_s + \beta_s' X_{ij})}{\sum_{j' \in C_i} \exp(\alpha_s + \beta_s' X_{ij'})} \tag{4.3}$$

$$M_i(s) = \frac{\exp(\gamma_s' Z_i)}{\sum_{s=1}^{s} \exp(\gamma_s' Z_i)} \tag{4.4}$$

where Z_i is a vector of segmentation variables consisting of individual socioeconomics and trip characteristics; γ_s is a vector of parameters for segment s $(s = 1, 2, ..., S)$. The choice probability for airline j consists of two terms. The choice probability within the segment $P_i(j|s)$ is the multinomial logit model, and the choice set C_i contains a set of alternatives including airline j. The probability of respondent i belonging to segment *(i.e., segment membership function)* is $M_i(s)$ which is also determined by using a standard logit formulation as functions of respondent's characteristics. For identification, segment membership coefficients for one of the segments are normalized to zero. Estimations of segment membership functions require specifying socioeconomic and trip variables. After parameter estimates are identified, the probabilities of each respondent belonging to each segment can be calculated, and each respondent is assigned to one of the segments on the basis of their largest probability. Subsequently, the size of each segment, as well as the profiles of respondents in each segment, can be obtained. Notably, our proposed latent class model, which is different from the one used by Teichert et al (2008), consists of segment membership functions that include individual socioeconomic and trip characteristics. The latent class model applied by Teichert et al., (2008) only included constant terms that were used to identify the size of segments.

Determination of the best number of segments requires a balanced evaluation of the indices such as BIC (Bayesian Information Criterion) and AIC (Akaike Information Criterion). The formulas are the follows:

$$AIC = -2LL + 2K \tag{4.5}$$

$$BIC = -2LL + (\ln(N))K \tag{4.6}$$

where LL is the value of log-likelihood function at convergence; K is the number of parameters in the model, and N is the total sample size. The latent class models with a different number of segments should be estimated and assessed. The BIC is often used in the latent class model because it imposes a harsher penalty on the number of parameters than the AIC and log-likelihood value (Walker and Li, 2007). Walker and Li (2007) further indicated that, AIC and BIC feature the same goodness-of-fit term, also the penalty term of BIC is more stringent than the penalty term of AIC (for $n = 8$, $k\ln n$ exceeds $2k$). Consequently, BIC tends to favor smaller models than AIC and AIC provides an asymptotically unbiased estimator of the expected Kullback discrepancy between the generating model and the fitted approximating model.

BIC provides a large-sample estimator of a transformation of the Bayesian posterior probability associated with the approximating model. By choosing the fitted candidate model corresponding to the minimum value of BIC, one is attempting to select the candidate model corresponding to the highest Bayesian posterior probability. In general, “smaller is better”: given two models, the one with the smaller AIC fits the data better than the one with the larger AIC. As with the AIC, a smaller BIC indicates a better-fitting model.

The latent class model, a finite mixture model for segmentation of choice data, produces a pre-specified number of latent classes which consists of the individuals who are assumed to be homogeneous with respect to their choice behavior or preferences (Wedel and Kamakura, 1998). The latent class model accounts for heterogeneity preferences for individuals by a number of segments while simultaneously identifying the size of segments and profiles of respondents. Both the latent class and mixed logit models account for preference heterogeneity across individuals, but two approaches differently capture variations of taste parameters (Greene and Hensher, 2003).

The latent class model accommodates parameter heterogeneity across individuals by using a discrete distribution as opposed to the assumption of continuous random variations in taste parameters used by the mixed logit model. The latent class model has been successfully applied to segment air passengers and identify preferences for air carriers across segments (Teichert et al., 2008). Consequently, the size of segments, as well as segment membership of respondents, can be identified.

4.3 Application

We used the poLCA package to estimate groups of passengers using a wide range of latent class models in R using a single command line, poLCA. Also included in the package is the command poLCA.simdata, which enables the user to create simulated data sets that match the data-generating process assumed by either the basic latent class model or the latent class regression model. This functionality is useful for testing the poLCA estimator and for performing Monte Carlo-style analysis of latent class models. The proper number of classes was assessed by BIC and AIC. Two, three and four-class solutions are reported in Table 4.1. For the model where the socio-economic characteristics are not included and not considered in the model, we called it a null model, whereas the model where the socio-economic characteristics were included and considered in the model, we called it socio-model. For the null model, the result reveals that as the number of classes increase, AIC decreases and BIC increase while for the socio-model, the result reveals that as the number of classes increases, both AIC and BIC decrease.

Further investigations were made to determine the model, among the two models, to be used to decide on the n-class solutions. Since the null model had lower BICs comparing to the other model, it was then decided that the n-class solution with the lowest BIC within the null model classes should be adopted. Therefore we adopted two-class solutions. This did not mean the models will be run without considering the socio-economic characteristics. Adding socio-economic in class membership resulted in different sizes of classes. The respondents were assigned to one of the two segments on the basis of their largest probability. In the null model, the size of class one is approximately 50.3% of the sample, which is different from 62.6% in class one of the socio model. Incorporation of individual characteristics in membership functions appears to change class sizes (Table 4.2).

For the null model, the coefficients of quantitative variables such as ticket price, airfare,

Table 4.1: Criteria for Determining the Optimal Number of Classes.

Models	Log-likelihood value	AIC	BIC
Null model			
2 classes	205.587	2213.324	2268.059
3 classes	163.162	2186.899	2270.825
4 classes	133.092	2172.829	2285.947
Socio model			
2 classes	1923.266	4796.507	4909.625
3 classes	1771.995	4677.236	4848.738
4 classes	1647.050	4584.291	4814.291

reason to fly, knowledge on LCC and general flying preference in class 2 are larger than those in class 1. In contrast, the respondent in class 1, have flown LCC before and are more sensitive to online services (see Table 4.2). The respondents in class 1 are less sensitive to Ticket price and fares relative to class 2. In addition, the respondents in class 2 have knowledge about LCC and they are more concerned about flying LCC than those in class 1. For the socio model, the coefficients of quantitative variables such as ticket price, flying in general, online services, government employee, adult and senior citizens are larger than those in class 2. Conversely, respondents in class 2 were more sensitive to fares, they fly for business purpose, know about LCC, tertiary educated compared to class 1. The results provide evidence that passengers in class 1 were married adults and senior citizens who are mostly government

Table 4.2: Estimation of Latent Class Analysis

		Null model		Socio model	
Variable description	**Variable (reference group)** †	**Class 1**	**Class 2**	**Class 1**	**Class 2**
Are tickets affordable?	TICKETPRICE (not affordable)	0.475	0.576	0.555	0.491
Do you consider fares?	FARES (yes it is consided)	0.301	0.420	0.315	0.434
Why do you fly most?	REASONTOFLY (Business)	0.126	0.235	0.152	0.226
Do you know LCCs?	KNOWLCC (yes)	0.037	1.000	0.444	0.623
Have you flown LCC before?	FLOWNLCC (yes)	0.748	0.000	0.427	0.302
What is your general preference?	FLYINGGENERAL (LCC)	0.566	0.639	0.652	0.519
Do you find online services convinient	OLINESERVICES (convinient)	0.916	0.858	0.910	0.849
Do you have tertiary education?	TERTIARY (yes)			0.545	0.689
Are you a government employee?	GOVEMPLOYEE (yes)			0.152	0.085
Are you a youth?	YOUTH (yes)			0.000	1.000
Are you an adult?	ADULT (yes)			0.809	0.000
Are you a senior citizen?	SNRCTZN (yes)			0.163	0.000
Namibian or Non-Namibian?	NATIONALITY (Namibian)			0.545	0.726
Male or Female?	GENDER (male)			0.584	0.585
Single or Evermarried?	MARITAL STATUS (single)			0.236	0.689
	CLASS SIZE (%)	50.35	49.65	62.70	37.30
	Maximum log-likelihod	-2367.254		-1091.662	

† Variable names have been explained in Table 3.1

employees and mostly non- Namibians. On the other hand, class 2 were single, Namibian youths, tertiary educated traveling for business purpose.

4.4 Conclusion

In conclusion, we observed that the null model associates class 2 with LCC and and class 1 with FSC. Consequently when socio-demographic variables were included in the model, it turned out completely the opposite, whereby socio model associates class 1 with LCC and class 2 with FSC.

Chapter 5

Discussions and Conclusions

This study was aimed at modelling the stated preference of air travellers choosing between two carriers (LCC and FSC) and it's determinants in order to propose the appropriate industry for passenger in Namibia. The two carriers are with contrasting operating structures. The results of this study indicated that passengers in Namibia have different preferences for the three fleets which were considered. Fleets which were looked at were short haul/ domestic, regional and long haul / international flights. The passengers' stated preference for domestic and regional flights was LCC whereas they preferred FSC for international flights. The results provided additional support to the notion that passengers' socio-demographics and behavioral choices (concerns about ticket prices, fares, online services and purpose journey) are important determinants. The ticket prices stood out as one of the main passengers' concern when they are making their preferences as to which carrier to use.

Passengers are of the opinion that for the domestic and regional flights, which are mostly short hauls and they are more interested in getting to their destination at a low ticket fare possible, regardless of the cabin service level as long as safety is guaranteed, and not really up for luxury services on board the plane. On the other hand, FSC is preferred on long hauls because of the comfort it brings with and luxury cabin services that become essential on long flights i.e. meals and comfort seat to sleep.

A quantitative cross- sectional study was engaged. We had no control over the exposure of interest which was passengers' stated preferences; we also measured a range of variables on individual passenger basis and at the same time measuring outcomes of interest. But due to the fact that this was more an observational study, the study tends to have a particular and pre-specified focus. We believe it had an effect on our results quality.

In a better designed preference study a discrete choice experiment are being used. A typical discrete choice experiment would have a range of items that a passenger would opt for i.e. price, time, safety, distance to the airport, parking etc. then this would involve permutations of these options. For instance if one takes price and time; one passenger can be offered low price with a morning departure or low price with an afternoon or low price with an evening departures. And then you permute, by offering another passenger with high price with similar combinations in terms of departure. Then a passenger would have to choose as per bundle of choices and different passengers will have different combinations. This is further enhanced by doing a randomization of these choices such that any two respondents may not be offered the same type of combination so that will eliminate any data quality issues and rigidity in terms of responses that may be available for the respondent.

Using binary data analysis and latent class analysis lead us to our results. These same methods were used in determining passengers' airline and/or airport choice by authors like

Ong and Tan (2010), Adler et al (2006), Bhat (1997) and Shirazian et al. (2012) just to mention a few. Their studies concluded that with the exception of education level and ethnicity, other socio-demographic characteristics do not play a statistically significant role in determining airline choice, instead behavioural factors such as concerns over schedules and fares, routes, booking methods and purpose of journey are found to be predictors of airline carrier choice. The probit applies when we are talking about latency because preference is something that you cannot just quantify as how a passenger prefers is not quantifiable as you are dealing with satisfaction therefore to try to measure preference level we used probit. On the other hand logit one is able to relate particular relations in terms of odds ratios.

These data analysis methods can be extended these models to include heterogeneity between respondents. We assumed that these respondents have a similar character when in fact they do not, the only difference if there is any; we had assumed that if will differ on the fixed effects, which is not actually the case in terms of preferences. A good extension would capture heterogeneity within preferences and across respondents. Most literature dealing with this have introduced random effects models or generalized estimating equations approach using Bayesian approaches (Crouchley, 1995). In some case multiple choices are possible and multinomial is involved.

Latent class models fitted taking in consideration the travelers' demographic and trip characteristics in the class membership, it not only improved the model fit but also allowed for distinguishing classes in terms of service attributes of airlines and testing the impact of socioeconomic and trip variables on class membership.

The use of such models can improve the understanding of how passengers select carriers and can assist the modeling and analysis of air travel demand. Furthermore, Latent class analysis indicated that, although majority want to fly LCC in general, due to passengers' profiles, two classes were identified. One class consists of educated youths who travel for business purpose and they are not government workers and mostly Namibians. On the other hand, the other group consists of adults and senior citizens who are mostly government employees not business travelers and mostly Non-Namibians. This implies that most Namibians fly out for business and this was evident from the high number of tickets which were bought by companies. On the other hand, adults and elders that are found at Namibia airports are mostly Non-Namibian, government workers and mostly on leisure trips.

The variables that we used we assumed exogeneity in the variables whereby we had a fixed set of variables explained pre-define set of choices. In many choice models, the assumption of exogeneity may not always hold because some of the variables can be mediating factors. This factor is not explored in this particular study This study is not without limitations. First due to limited time and resources the sample size was small and was only selected from two Windhoek, Namibia airports; Hosea Kutako International Airport and Eros Airport. Other airports from different towns in Namibia were not considered. Secondly, this is more an observational study therefore the study tends to have a particular and pre-specified focus. Human beings are the topic of the study hence the focus is typically on a certain aspect of behavior which is preference. Finally, discrete choice experiment would have given us better conclusions but it is not possible in this case. Instead it was a basic cross-sectional experiment which did not adhere to discrete choice experiment which often presents a set of choices.

In conclusion, this study strongly indicated that passengers in Namibia are not willing to pay high fares for air tickets. Given the aspect of education level, income level, reason for travel, ticket fares, occupation, gender and age being found to be the determining factors of airline carrier choice, by introducing LCC may increase the base of potential customers. Another form of increasing the demand may be introducing promotional combos, such as one price would include the air ticket, hotel accommodation, car hire, just as an example, to just motivate people to fly. Their studies concluded that with the exception of education level and ethnicity, other socio-demographic characteristics do not play a statistically significant role in determining airline choice, instead behavioural factors such as concerns over schedules and fares, routes, booking methods and purpose of journey are found to be predictors of airline carrier choice.

However, passengers in Namibia are currently only exposed to one scheduled type of carrier, which is full service carrier and a national carrier. The possible LCC carrier is expected to start operations between Windhoek and Johannesburg in April 2015. The respondents indicated that flying in Namibia is expensive and the most Namibians that fly are those that are flying for business purpose, on their companies costs. It is such that business travelers are not concerned about the fares but rather time that they are saving when they fly comparing to spending hours on the roads driving. This is justified by the size of the aircraft that the National carrier is operating with on the domestic routes, which is a small jet-37 seater. The interviewed group indicated that they find air tickets not affordable and these prices are really a big concern to them and if LCC with low prices were introduced in Namibia then many would consider flying. Namibians have indicated that only few have knowledge on LCC and most of them have not tried them before. Non-Namibians indicated that they know about

LCC, they use them and they prefer them on short haul flights. In this thesis we modeled the stated preferences of air travellers in Namibia, we identified the determinant that inform the choices and the study therefore concluded that based on the interviewed passengers' profiles, the best and appropriate carrier in Namibia is a low cost carrier.

Further studies may explore the endogeneity principles, individual heterogeneity and linearity in the variables. It is also worth exploring discrete experiment.

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Appendix

A.2-1 SPSS commands

A.2-1 Table 2.1

CROSSTABS /TABLES=EDULEVEL INCOME$_{S}OURCEBYGENDER$

$/FORMAT = AVALUETABLES$

$/CELLS = COUNTROWCOLUMNTOTAL$

$/COUNTROUNDCELL.$

A.2-2 Figure 2.1

CROSSTABS /TABLES=WHYAIRLINESPC BY NATIONALITY

/FORMAT=AVALUE TABLES

/STATISTICS=CHISQ

/CELLS=COUNT ROW

/COUNT ROUND CELL

/BARCHART.

A.2-3 Figure 2.2

CROSSTABS

/TABLES=GENERALFLIGHT BY GENDER

/FORMAT=AVALUE TABLES

/STATISTICS=CHISQ

/CELLS=COUNT ROW

/COUNT ROUND CELL

/BARCHART.

A.2-4 Table 3.1

/DESCRIPTIVES VARIABLES=WHYTHEAIRLNGEN FLYMOSTLCCFSC WHYAIRLINESPC TICKETPAYER

/RESERVTNPOINT ONLINESVCS LONGHAULS DOMESTIC REGIONAL GENERALFLIGHT NATIONALITY GOVERMENT TERTIARYEDU

/INCOM1 INCOM2 INCOM3 MARITALSTATUS GENDER YOUTH ADULT SENIORCITIZN

/FLYREASON ONLINECONVINIENT

/STATISTICS=MEAN STDDEV MIN MAX.

A.2-5 Table 3.2

CROSSTABS

/TABLES=NATIONALITY GENDER EDULEVEL MARITALSTATUS BY DOMESTIC REGIONAL

GENERALFLIGHT INTERNATIONAL

/FORMAT=AVALUE TABLES

/STATISTICS=CHISQ

/CELLS=COUNT ROW COLUMN TOTAL

/COUNT ROUND CELL.

A.2-2 R commands

A.2-1 Logit model commands

$>$ LOGD=read.table("clipboard",header=TRUE)

$>$ logg1 = glm(DOMESTIC $\sim FARES + FLYREASON + TERTIARY + YOUTH + ADULT + SNRCTZN + MARITAL_STATUS + GENDER + GOVEMPLYEE + NATIONALITY + ONLINECONV + INCOM1 + INCOM2 + INCOM3, family = binomial, data = LOGD)$

$>$ summary(logg1)

$>$ logg2 = glm(REGIONAL $\sim FARES + FLYREASON + TERTIARY + YOUTH + ADULT + SNRCTZN + MARITAL_STATUS + GENDER + GOVEMPLYEE + NATIONALITY + ONLINECONV + INCOM1 + INCOM2 + INCOM3, family = binomial, data = LOGD)$

$>$ summary(logg2)

$>$ logg3 = glm(INTERNATIONAL $\sim FARES + FLYREASON + TERTIARY + YOUTH + ADULT + SNRCTZN + MARITAL_STATUS + GENDER + GOVEMPLYEE + NATIONALITY + ONLINECONV + INCOM1 + INCOM2 + INCOM3, family = binomial, data = LOGD)$

$>$ summary(logg3)

$>$ logg4 = glm(GENERALFLY $\sim FARES + FLYREASON + TERTIARY + YOUTH + ADULT + SNRCTZN + MARITAL_STATUS + GENDER + GOVEMPLYEE + NATIONALITY + ONLINECONV + INCOM1 + INCOM2 + INCOM3, family = binomial, data =$

$LOGD)$

$>$ summary(logg4)

$>$ confint(logg1)

$>$ confint(logg2)

$>$ confint(logg3)

$>$ confint(logg4)

$>$ exp(coef(logg1))

$>$ exp(coef(logg2))

$>$ exp(coef(logg3))

$>$ exp(coef(logg4))

A.2-2 Probit model commands

$>$ LOGD=read.table("clipboard",header=TRUE) $>$ prob1 = glm(DOMESTIC $\sim FARES+FLYREASON+TERTIARY+YOUTH+ADULT+SNRCTZN+MARITAL_STATUS+GENDER+GOVEMPLYEE+NATIONALITY+ONLINECONV+INCOM1+INCOM2+INCOM3, family=binomial(link="probit"), data=LOGD)$

$>$ summary(prob1)

$>$ prob2 = glm(REGIONAL $\sim FARES+FLYREASON+TERTIARY+YOUTH+ADULT+SNRCTZN+MARITAL_STATUS+GENDER+GOVEMPLYEE+NATIONALITY+ONLINECONV+INCOM1+INCOM2+INCOM3, family=binomial(link="probit"), data=LOGD)$

$>$ summary(prob2)

$>$ prob3 = glm(INTERNATIONAL $\sim FARES+FLYREASON+TERTIARY+YOUTH+ADULT+SNRCTZN+MARITAL_STATUS+GENDER+GOVEMPLYEE+NATIONALITY+ONLINECONV+INCOM1+INCOM2+INCOM3, family=binomial(link="probit"), data=LOGD)$

$>$ summary(prob3)

$>$ prob4 = glm(GENERALFLY $\sim FARES+FLYREASON+TERTIARY+YOUTH+ADULT+SNRCTZN+MARITAL_STATUS+GENDER+GOVEMPLYEE+NATIONALITY+ONLINECONV+INCOM1+INCOM2+INCOM3, family=binomial(link="probit"), data=LOGD)$

$>$ summary(prob4)

$>$ confint(prob1)

$>$ confint(prob2)

$>$ confint(prob3)

$>$ confint(prob4)

$>$ exp(coef(prob1))

$>$ exp(coef(prob2))

$>$ exp(coef(prob3))

$>$ exp(coef(prob4))

A.2-3 Latent class model commands

A.2-1 Null models

$>$ mod4w = poLCA(cbind(TICKETPRICE=TICKETPRICE+1,FARES=FARES+1, REASONTOFLY=REASONTOFLY+1,KNOWLCC=KNOWLCC+1,FLOWNLCC=FLOWNLCC+1, FLYINGENERAL=FLYINGENERAL+1,ONLINESERVICES=ONLINESERVICES+1) $\sim 1, maxiter = 50000, nclass = 4, nrep = 10, data = LATk)$

$>$ mod3w = poLCA(cbind(TICKETPRICE=TICKETPRICE+1, FARES=FARES+1,REASONTOFLY=REASONTOFLY+1,KNOWLCC=KNOWLCC+1,FLOWNLCC=FLOWNLCC+1, FLYINGENERAL=FLYINGENERAL+1,ONLINESERVICES=ONLINESERVICES+1) $\sim 1, maxiter = 50000, nclass = 3, nrep = 10, data = LATk)$

$>$ mod2w = poLCA(cbind(TICKETPRICE=TICKETPRICE+1, FARES=FARES+1,REASONTOFLY=REASONTOFLY+1,KNOWLCC=KNOWLCC+1,FLOWNLCC=FLOWNLCC+1, FLYINGENERAL=FLYINGENERAL+1,ONLINESERVICES=ONLINESERVICES+1) $\sim 1, maxiter = 50000, nclass = 2, nrep = 10, data = LATk)$

A.2-2 Socio models

$>$ mod4 = poLCA(cbind(TICKETPRICE=TICKETPRICE+1, FARES=FARES+1, REASONTOFLY=REASONTOFLY+1, KNOWLCC=KNOWLCC+1, FLOWNLCC=FLOWNLCC+1, FLYINGENERAL=FLYINGENERAL+1, ONLINESERVICES=ONLINESERVICES+1, TERTIARY=TERTIARY+1, GOVEMPL0YEE=GOVEMPL0YEE+1, YOUTH=YOUTH+1, ADULT=ADULT+1, SNRCTZN=SNRCTZN+1, NATIONALITY=NATIONALITY+1, GENDER=GENDER+1, MARITALSTATUS=MARITALSTATUS+1) $\sim 1, maxiter = 50000, nclass = 4, nrep = 10, data = LATk)$

$>$ mod3 = poLCA(cbind(TICKETPRICE=TICKETPRICE+1, FARES=FARES+1,REASONTOFLY=REASONTOFLY+1, KNOWLCC=KNOWLCC+1, FLOWNLCC=FLOWNLCC+1, FLYINGENERAL=FLYINGENERAL+1, ONLINESERVICES=ONLINESERVICES+1, TERTIARY=TERTIARY+1, GOVEMPL0YEE=GOVEMPL0YEE+1, YOUTH=YOUTH+1, ADULT=ADULT+1, SNRCTZN=SNRCTZN+1, NATIONALITY=NATIONALITY+1, GENDER=GENDER+1, MARITALSTATUS=MARITALSTATUS+1) $\sim 1, maxiter = 50000, nclass = 3, nrep = 10, data = LATk)$

$>$ mod2 = poLCA(cbind(TICKETPRICE=TICKETPRICE+1, FARES=FARES+1,REASONTOFLY=REASONTOFLY+1, KNOWLCC=KNOWLCC+1, FLOWNLCC=FLOWNLCC+1, FLYINGENERAL=FLYINGENERAL+1, ONLINESERVICES=ONLINESERVICES+1, TERTIARY=TERTIARY+1, GOVEMPL0YEE=GOVEMPL0YEE+1, YOUTH=YOUTH+1, ADULT=ADULT+1, SNRCTZN=SNRCTZN+1, NATIONALITY=NATIONALITY+1, GENDER=GENDER+1, MARITALSTATUS=MARITALSTATUS+1) $\sim 1, maxiter = 50000, nclass = 2, nrep = 10, data = LATk)$

A.2-3 Study questionnaire

QNR #

My name is Alisa Amwaama. I am pursuing my master’s degree in applied statistics and demography at the University of Namibia. My research topic is on modeling stated choices and preferences of air travelers towards determining the best airline business in Namibia. I would like to ask your opinion on choices and preferences by means of filling in this questionnaire. I am therefore humbly asking you to be so kind to fill in this questionnaire to the best of your knowledge. Your responses will be kept confidential and will strictly be used for this study only. Please do not write down your name for anonymous reasons. Please answer all the questions.

1	With which airline are you flying today?			name the airline		
2	Why do you choose to flying with the above mentioned airline?					
Always fly it		Cheap fare	Convenient	Other: Specify		
3	Which other airline do you fly most?					
SAA		SA express	Air Namibia	Emirates	BA	Lufthansa
Mango		Kulula	Other: Specify			
4	How many times did you fly in the past 12 months					
<2		2 to 5	6 to 9	> 10		
5	What is the reason you fly most of the time					
Leisure		Business/Work				
6	Why do you choose a specific airline?					
Reliability		Ticket price	Service quality	Frequent flier program	Your company policy	
7	What type of ticket do you use most?					
Rebate		Reward	Discount	Company cost	Full cost	
8	Rate the price of this airline's ticket?					
Low		Affordable	Not affordable	Extremely high		
9	Who paid for your ticket?					
Myself		Company	Someone else			
10	How would you rate the service on board compared to the ticket price					
Very satisfied		Fair satisfied	Neutral	Dissatisfied	Very dissatisfied	
11	Where did you check in your flight?					
Airport		Telephone	Online	Other: Specify		
12	Which channel did you use for reservations?					
Online		Travel agent	Tour operator	Call center		
13	How convenient is it to use online services?					
Very convenient		Convenient	Neutral	Not Convenient	Very Not Convenient	
14	How comfortable are you when using online servises?					
Comfortable		Not comfortable				
15	Are you an airline employee or agent?					
	Yes	No				
16	How satisfied are you with the value of your money on flights?					
Very satisfied		Fair satisfied	Neutral	Dissatisfied	Very dissatisfied	
17	How many connections between initial departure and final destination?					
None		One	Two	Three	Four	Five or more
18	Have you ever heard of Low cost airlines?					
Yes		No	*if **No** proceed to 21*			
19	Can you differentiate between Low cost airline and Full service airlines?					
yes		no				
20	Have you flown Low cost airlines before?					
Yes		No				

21 **Definitions:**
***Low cost airlines:* generally has lower fares and fewer comforts.**
***Full service airlines* are that operate what are referred to as "hub-and-spoke" systems through which they funnel passengers from different locations into central hubs at major airports and sort the passengers onto connecting flights to their ultimate destinations.**

22 What would you prefer for long haul flights?

Low cost airlines	Full service airlines

23 What would you prefer for short haul flights?

Low cost airlines	Full service airlines

24 What would you prefer for domestic flights?

Low cost airlines	Full service airlines

25 What would you prefer to for regional flights?

Low cost airlines	Full service airlines

26 What would you prefer for international flights?

Low cost airlines	Full service airlines

27 What would you prefer when travelling for leisure?

Low cost airlines	Full service airlines

28 What would you prefer when travelling for business?

Low cost airlines	Full service airlines

29 What would you prefer when travelling with luggage?

Low cost airlines	Full service airlines

30 What would you prefer when travelling with children?

Low cost airlines	Full service airlines

31 In general what would you prefer to fly?

Low cost airlines	Full service airlines

32 Wat is your nationality?

Namibian	Non-Namibian

33 What is your occupation?

Senior Official/ CEO	Middle Management	Administrative/ Office	Professional	Technical/ Craft person	Sales/ Buyer
Self employed	Govt./Military	Homemaker	Student	Retired	Other: Specify

34 What is your level of education?

Lower	Higher	Tertiary

35 What is your monthly income in Namibia Dollars?

<5000	5000-9999	10000-19999	20000-29999	30000-39999	>40000

36 What is your source of income:

Self employed	Employed	Pension	Dependent	Other: specify

37 How would you describe your economic status?

Poor	Below avearage	Average	Above average	Well off

38 How would you describe your ethinicity?

Black	White	Coloured	Indian/Asian

39 How would you describe the area in which you are residing?

Urban	Rural

40 What is your marital status?

Single	Married	Separated	Divorcee	Widowed

41 Gender

Male	Female

42 How old are you?

<15	15-24	24-34	34-44	44-54	>54

End of Questionnaire

Thank You Very Much For Your Time !!!