Estimation of Route-Based Air Travel Demand Elasticities in Nigeria

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Abstract- **Air travel demand modelling is important to planning, design, and operations. This research developed an air travel demand model for Nigeria domestic network. Using panel data from period of 2009 to 2013, the model captured both time series and cross-sectional variation of air travel demand. The empirical analysis explicitly modelled service variables by a log-linear demand model using OLS estimation. prefer routes with high flight frequency. The coefficient of scheduled flight time indicates, travelers prefer routes with shorter scheduled flight time. In addition, the coefficients for on-time performance variables are statistically significant. Almost income elasticities estimates are less than 1, implying, air demand is income inelastic in most Nigerian markets. No specific markets time trends for scheduled flight time and fare effects are found. This study provides a framework for airlines to estimate demand on domestic routes operated to ensure business sustainability.**

Key Words- **air travel, demand, elasticity, route-based and panel estimation.**

The estimates yielded better demand elasticities than those of direct linear models. Empirical findings include; at market level, fare elasticities from the estimates indicate inelastic market demand. Except for routes with connecting flights, which is highly elastic with fare elasticity value of -2.932. All estimated frequency coefficients indicates, potential travelers

I. INTRODUCTION

Numerical study on passengers' travel demand in air transport network has rarely been seen both in research literature and in industry training in Nigeria. Hence, immediate attention is needed by airlines on decision making on how to amend their structures to improve their tasks. Demand forecasting is the means of assessing the estimated number of travelers on individual scheduled flight in the market environment of other competitors.

Researchers have observed different aspects of assessing air travel demand ([6], [44], [22], [1]). The study of [6] widened the knowledge of dimensions of air travel. The basic outcomes of their study are that (1) air travel to all foreign destinations is highly elastic in income and inelastic in price and (2) there is no difference between demand elasticity, financial and non-financial assets, and that both are inelastic [3].

[51] Research work on air travel demand modelling started in 70s by [17], [19] and [49]. Estimated demand models based on concept of ''schedule delay'', a function of aircraft size and service frequency. Later on, [50], [4] and [46] estimated air travel demand models based on generic term, ''service quality'', which is a function of airline service variables, as aircraft size, service frequency, and ticket price. [21], [39] develop gravity-like demand models, taking social-economic and demographic factors as local income and population into consideration. Air travel demand models also, estimated from a microscopic perspective. [38] estimated a probabilistic air travel demand model based on assumption that passengers' desired departures are uniformly distributed. [37] assumes that passenger demand during a specific time period is a function of distribution of departures of all flights. Researchers as [33], [28], [13] suggests that it is important to incorporate travel time reliability/variability in model specification.

Logit model has been used extensively in the research works of air travel demand. [31], [27], [16], [43], and [4] construct demand models or market share models as logit-based functions of service frequency, service quality, ticket price, etc. [45] and [35] estimated logit models based on survey data from individual passenger. [14] apply the aggregate multinomial logit methodology, estimated an itinerary-level market share model. [29] used similar model to estimate market share, incorporating joint probability density distribution functions of time value and frequent flyer membership in utility function. There are many research works; hence the 1990's style series of models to model air passenger numbers. The modelling performance of each model varies based on country's origin of passengers. The flights considered (domestic, trans-border, international), the performance measure and modeling horizon ([18], [41], [12]). No methodological approach found to always dominate another in terms of modelling performance out-of-sample [47].

Recently, combination modelling techniques have become popular in the modelling literature as means of improving modelling performance, to control for the uncertainty of relying exclusively on single model. In tourism modelling literature, single model combinations are found to outperform the specific models being combined, independently of time horizon considered ([47], [15], [48]). However, these results are sensitive to the combination technique ([52], [15]) same as region/country-specific characteristics (Wong et al., 2007).

Finally, the best performance might be achieved by combining two or three single models at most [52]. [7] compared modelling performance of a Holt-Winters exponential smoothing model, a univariate time series model (ARIMA) and support vector machines based models. [20] made use of wide variety of multivariate models to study air traffic demand between United Kingdom and five other countries: Germany, Sweden, Italy, the USA and Canada. [25] developed two gravity models as to model air passengers between city pairs. Both models include geo-economic variables. The semi-logarithmic regression model for estimation of domestic passenger volume between domestic cities in Turkey was examined by [40].

Correct identification of causal factors and quantifying their effects contribute to fundamental understanding of air travel demand and allow estimation of demand with regards to wide range of future scenarios, including different levels congestion; network connectivity, aircraft size, frequency, and fuel price, etc. Existing models are not sufficient to meet these objectives for several reasons. Changes in structure of air travel demand are of interest and seldom studied. Transformational development of internet and its use to purchase air travel may affect structure of airline service demand by increasing availability of travel information and reducing roles of travel agents. Entry of low cost carriers in Nigeria; Aero Contractor and the newly established Air Peace may increase expectations for lower fares and tendency of consumers to search for them. Examining trends in structure of air travel demand can reveal whether and to what extent such changes have occurred, and thereby reveal future of air travel behaviours in Nigeria.

The aim of this paper is to estimate route based air travel demand elasticities in Nigeria that can be used by airlines to evaluate overall travel demand and to see how demand changes, if any of airlines' service variables are adjusted. Two other aspects that are critical to process of modelling air passenger demand in Nigeria: modelling air passenger trip generation at route-based level, and forecasting how airline services are expected to evolve.

II. STUDY BACKGROUND

This paper models route-based air travel demand. Generally, potential trips between two cities are derived from the socioeconomics activities in both cities. Potential travelers may have choices regarding these potential trips. They may avoid air travel by choosing different modes, or they may not to travel at all. They may select different routes, of which airports and segments (non-stop links) are basic elements. Thus, route selection involves choices of airports (origin, destination, and connecting airports) and segments. A change in characteristics of route may affect the attractiveness of this route, or of list of routes, because different routes in a market may share the same airports and/or segments. Aggregate air demand in a route-based market may also be affected by changes in individual route characteristic or that impact routes across air travel market.

Models of air travel demand are important inputs for wide variety of economic decisions, including; not limited to, research and development, airplane design and production planning. For product like air travel, where interest lies in aggregate demand, the typical empirical practice is to obtain national level model using aggregate level data when individual market data are less accessible [32]. However, [9] has shown that individual markets are more heterogeneous, even for national products which are sold in distinct markets, as the case for air travel. An aggregate approach is preferable to a disaggregate approach when computational/analytical burden of producing models for separate markets is substantial. Furthermore, more concerns in a disaggregate approach, the number of parameters estimated by modeling each market individually quickly becomes large relative to length of available time series [11]. However, the econometric arguments in favor of a disaggregate approach are also fairly strong when disaggregate data are available. [5] review the literature on advantages of using disaggregate data, one of which is additional information available due to heterogeneity across individual markets. However, they argue that the relative performances of aggregate and disaggregate approaches might depend on specifics of modelling exercise.

This paper focuses on exploring effect of aggregate information on the accuracy of aggregate air travel demand models. This paper considers the case of Nigeria commercial air travel demand. The data available from the NCAA are the quarterly flight information departing from all airports between 2009 and 2013. Individual route level data for 117 flight routes was used during the period under study, together with aggregate level data.

Specifically, the paper considered modelling a variable that is a contemporaneous aggregation of the individual subcomponents at time t:

$$y_t = \sum_{n=1}^{N} yit \quad for\ t = 1,2 \ldots \quad \text{where } yit\ (I = 1,2 \ldots N)$$

The subcomponent of aggregate variable is y_{it}. Models of the aggregate variable can be obtained using two different approaches: (1) estimating reduced-form model for aggregate variable using aggregate level data, then forming models of aggregate variable from estimated model; or (2) estimating reduced-form model for subcomponents using individual level data, forming models of subcomponents from estimated individual models, then aggregating subcomponent models to obtain the model of aggregate variable. Not only does second approach use more information, but also models at disaggregate level are readily available, whereas one needs to allocate aggregate model to individual markets to obtain models at disaggregate level in first approach. This paper analyzed the out-of-sample model performances of these two extreme approaches in modelling aggregate variable, along with performances of other approaches that are between these two extremes.

[11] examined revival of interest in contemporaneous aggregation of aggregate macroeconomic indices as economic variables. The functional form selected for estimating model is log-linear. The relationship between demand for air travel *D* and explanatory variables disaggregate models to form models of an aggregate variable in both theoretical and empirical econometrics literature. The empirical literature focused mainly on modelling is assumed to take the following functional form:

$$D = A \cdot \prod_{g} G_{g}^{\beta_g} \cdot \prod_{s} S_{s}^{\gamma_s}$$

Where A is constant, and G_g and S_s represent geo-economic and service-related factors, respectively. Taking logarithm on both sides, equation above becomes linear in the exponents of factors. This allows the use of linear regression techniques for analysis. The values of the parameters represent variation rate of the demand with respect to percentage variation of corresponding factors, all other conditions being equal. This captures the concept of elasticity.

Direct demand estimation was done using ordinary least squares (OLS), taking into account usual drivers affecting passenger air travel demand. Literature provides many research works where determinants of air travel demand are investigated and methodologies assessing their influence are proposed. Studies in this field includes; [4], [21], [23], [30], [1], [10], [50], [53]. The study of [21] presents econometric air travel demand model for entire conventional domestic network of Norway. In addition to population and income factors, airfares, travel time and inter-modal competition factors are taken into account, short-medium and long term demand elasticities are estimated. Demand results inelastic in short-medium term (estimated elasticity: -0.69) and elastic in long term (estimated elasticity: -1.63) with respect to airfares and elastic with respect to travel time.

The study of [23], presents an econometric model for the intercity air travel demand in USA. The model incorporates some quality of service measures as explanatory variables and coefficients are estimated using post-deregulation data. A distinction is made between services offered by airlines in peak and off-peak hours and dummy variable is introduced for capacity-constrained airports. The research has it that demand is elastic with respect to airfare (estimated elasticity: -1.2) and highly dependent on flight schedule and travel time. [10] present meta-analysis of price elasticity estimates of demand for passenger air travel. After a description of determinants of demand for passenger air transport, they carry out a comparative re-evaluation of previous research on price elasticities for passenger air transport. They find an overall demand mean price elasticity of -1.146 with passengers becoming price sensitive over time. Business passengers show lower price sensitivity, with an average price elasticity of -0.8. Passengers are becoming price sensitive over time.

III. ESTIMATION MODEL

The data for this study were assembled from secondary sources. To estimate the model, this research compiled panel data set including variables for all Nigerian domestic routes over 2954 quarters- all quarters between year 2009 and 2013. The raw data is from five sources: (1) NCAA Airline Origin and Destination Survey; (2) NAMA flight strip data; (3) FAAN; (4) Airlines operational in Nigeria; and (5) Online Airport/Airlines operational data. In order to simplify empirical work and/or get reliable data, it was filtered. Market level variables, which are used to explain total demand of air routes, are identical for all air routes of a market. The statistics for variables, therefore, are presented in terms of routes. This research uses Nigerian domestic itineraries with non-zero flight data and was further filtered by excluding routes with less than twelve (12) flights per quarter. These itineraries account for about 95% of all Nigerian domestic itineraries.

Assuming, potential travelers are homogeneous in the observed characteristics-no individual deviations ($\mu_{irt} = 0$) except for the stochastic terms ε_{irt}'s, the equations to estimate determinants of demand of domestic traffic in the sample of Nigerian airports within the period under study are as follows. Following analytical specification, it specifies the following equation for estimation in semi-logarithmic form:

Model 1:

$$InD_{totpax} = \beta_1 InFreq + \beta_2 InFare + \beta_3 Rtyp + \beta_4 InOntp + \beta_5 InDist + \beta_6 InScft + \beta_7 InInco + \varepsilon_{irt}$$

Model 2**:**

$$InD_{pax-km} = \beta_1 InFreq + \beta_2 InFare + \beta_3 Rtyp + \beta_4 InOntp + In\beta_5 Scft + In\beta_6 Inco + \varepsilon_{irt}$$

The explanatory variables are defined as follows:

$Freq$ = represents the frequency of flight at route r;

$Fare$ = available airline fare of route r, which is the same for all routes of the O-D airport pair at time t served by the same airline;

$Rtyp$ = is the binary indicator variable for the direct route; 1 if a route is a direct route, 0 if otherwise

$ontp$ = on-time performance of flights of respective airlines

$Dist$ = distance between origin and destination

$Scft$ = scheduled flight time of respective route-specific flight

$Inco$ = Gross domestic product per capita (income determinant of travelling public)

By treating the regression function coefficients as elasticity coefficients, hence, estimated log-log relationship between air travel demand (measured as passenger-kilometres) and the explanatory variables. This logarithmic transformation has benefit of reducing risk of heteroscedasticity ([26], [8], [34]) although it does not completely eliminate it. As stated by [34], to estimate a regression model: "One of the assumptions we have made is that errors u_i in the regression equation have a common variance σ^2. This is known as the homoscedasticity assumption. If the error does not have a constant variance, we say they are heteroskedastic" [34]. Thus, heteroscedasticity means that model is not convergent, making it less robust.

1V. ESTIMATION RESULTS

Elasticity is a useful tool in demand analysis. As a result, estimates of air travel demand elasticities, especially with respect to fare, is found in the literature on transport studies. Comparing demand elasticities from our models to previous estimates help assess model validity. Elasticity, is dimensionless, also provides a convenient way to compare relative importance of causal factors. This is particularly useful for log-linear models, since estimated coefficients are elasticity values. This research estimates utilized structural demand equations models in logarithmic forms consistent with econometric modelling. The detailed estimation results, are discussed by airlines (selected with reasonable traffic share of above 4% within the study period 2009-2013) and then are combined in the summary in which results of OLS model with the same explanatory variables are also presented for comparison purpose (see Table 1).

TABLE 1
SUMMARY OF AIRLINES FLIGHT DATA PER QUARTER

Airline	**Freque ncy**	**Percentage route share**
AERO	488	16.5
AFRIJET	17	0.6
AIR NIGERIA	235	8.0
ARIK	1147	38.8
ASSOCIATED	160	5.4
BELLVIEW	16	0.5
CAPITAL	13	0.4
CHANCHANGI	112	3.8
DANA AIR	173	5.9
FIRST NATION	13	0.4
IRS	325	11.0
MEDVIEW	37	1.3
OVERLAND	218	7.4
Total	2954	100

Source: Authors' Compilation (2015)

As shown in Table 2, most coefficients of explanatory variables are statistically significant and have expected signs. Thus service variables impacting on air travel demand are not correlated but distinct in attributes.

TABLE 2
PANEL DATA ESTIMATION RESULTS FOR AGGREGATE AIR TRAVEL DEMAND

Variable	**Model 1**	**Model 2**
Frequency (flights per quarter)	**1.339*** [0.012]**	**1.337*** [0.013]**
Scheduled Fight Time (minutes)	**-1.003*** [0.183]**	**2.375*** [0.145]**
On-time Performance (minutes per flight)	**-0.855*** [0.161]**	**-1.146*** [0.178]**
Fare (in Naira)	**-0.062 [0.089]**	**-0.319*** [0.048]**
Income (measured in GDP per capita in Naira)	**-0.107* [0.053]**	**0.193*** [0.057]**
Routing Type (=1, if direct route)	**0.033 [0.069]**	**0.220** [0.076]**
Route Distance (kilometres)	**0.924*** [0.073]**	
Constant	**6.831*** [0.960]**	9.551*** **[1.061]**
R^2	*0.826*	*0.806*
Adjusted R^2	*0.825*	*0.805*
F	*929.364*	*871.302*

1. Model 1: Dependent variable = In (Total Number of Passengers); 2. Model 2: Dependent variable = In (Passenger-Kilometres); 3. Standard errors in brackets are robust to heteroskedasticity and serial correlation;
4. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Statistics of the first stage.

TABLE 3
PANEL DATA ESTIMATION RESULTS- MODEL 2 ESTIMATES WITH ROUTING BIAS

Variable	**Direct Flight**	**Connecting Flight**
Frequency (flights per quarter)	**1.352*** [0.013]**	**0.774*** [0.116]**
Scheduled Fight Time (minutes)	**1.878*** [0.148]**	**0.495 [3.968]**
On-time Performance (minutes per flight)	**-0.176 [0.193]**	**-3.127 [3.172]**
Fare (in Naira)	**-0.324*** [0.097]**	**-2.932*** [0.842]**
Income (measured in GDP per capita in Naira)	**0.147** [0.057]**	**0.281 [0.285]**
Constant	**7.360*** [1.045]**	**-6.829 [6.032]**
R^2	0.823	0.384
Adjusted R^2	0.822	0.322
F	1001.840	6.133

1. Model 2: Dependent variable = In (Passenger-Kilometers); 2. Standard errors in brackets are robust to heteroskedasticity and serial correlation; 3. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$; Statistics of the first stage.

All estimated fare coefficients illustrate positive fare impacts on demand, the fare coefficients from Model 2 estimates are more reasonable. Fare coefficients from Model 2 estimations are larger (in absolute values) than those from Model 1 estimations. All estimated frequency coefficients indicate, potential travelers prefer routes with high flight frequency. The results confirms, the causal factors are critical to airline service demand in Nigeria, thus a proportional flight frequency increase on segment with lower frequency increases service attractiveness more than an equivalent change on higher frequency segment. Coefficients of scheduled flight time indicates, travelers prefer routes with shorter scheduled flight time, only the Model 2 estimates suggest significantly different marginal effects for different routing types. The Model 2 estimates show a one-minute increase of scheduled flight time on routes have a larger (1.878 times) impact of utility on direct routes. This result has two explanations. First, travelers may feel more comfortable spending time on direct flights than on connecting ones. For example, they do not have to worry about missing their subsequent flights due to flight delay and/or finding gates. Second, there may be nonlinear effects of flight time that translate into the observed differences in coefficient estimates. Given a route-based market, scheduled flight time of connecting route is normally greater than a direct route. The nonlinear effects would make travelers less likely to choose a connecting route with flight time longer than a direct route.

A. Demand Elasticity with respect to Fare

Fare elasticities of route demand are summarized in Table 4. Since potential travelers have more route choices, fare elasticities of route demand are expected to be larger (in

values). While the fare elasticities calculated from OLS estimates, are consistent with expectation. In addition, when market size (measured by passengers' number) is taken into account, the elasticities become smaller in absolute values. Details of these elasticities are discussed below.

TABLE 4
FARE ELASTICITY OF VARIOUS AIRLINES

Airline	**Fare Elasticity**	**Remark**
ARIK	-0.151	inelastic
AERO	-0.240	inelastic
ASSOCIATED	-0.097	inelastic
CHANGCHANGI	-0.387	inelastic
DANA	-1.159	elastic
IRS	-0.357	inelastic
OVERLAND	-0.280	inelastic
AIR NIGERIA	-1.740	elastic
Aggregate (panel)	-0.319	inelastic

Source: Authors' Compilation (2015)

The fare elasticities can be investigated by their distributions and compared with other estimates in literature. The fare elasticities from OLS estimates indicate inelastic market demand except for Dana and Air Nigeria which showed elastic values. This indicates that fare elasticities of low traffic markets are higher than those of high traffic markets. A possible reason is, current fares in low traffic markets are relatively high. Thus, a proportional fare increase reduces more service attractiveness in these markets. Direct comparisons of estimates from literature and this research cannot be made because most fare elasticities available in literature are estimates for air market demand or for airline demand. However, guidelines for ranges of fare elasticities are available (see Table 5).

One would expect, elasticities of route demand should be larger (in absolute values) than those of market demand, since people have higher flexibility in air routes as long as they arrive their destinations, and changing to other modes or trip cancelations are less likely to be their choices. Summarizing from the literature on air market demand, [24] reported, the medians of the fare elasticities for different trip lengths and trip purposes range from -0.70 to -1.52. The fare elasticities of route demand from OLS estimates are, like those of market demand, too low- most of them are smaller (in absolute values) than those of market demand from [24]. For example the market aggregated level, the elasticities of -0.062 and -0.319 were computed at Model 1 and Model 2 respectively.

TABLE 5
ESTIMATED FARE ELASTICITIES OF PASSENGER DEMAND

	Route/Market level		**National level**		**Supra-national level**	
	Short-haul	**Long-haul**	**Short-haul**	**Long-haul**	**Short-haul**	**Long-haul**
Intra N America	-1.5	-1.4	-0.9	-0.8	-0.7	-0.6
Intra Europe	-2	-2	-1.2	-1.1	-0.9	-0.8
Intra-Asia	-1.5	-1.3	-0.8	-0.8	-0.6	-0.6
Intra Sub-Saharan Africa	-0.9	-0.8	-0.5	-0.5	-0.4	-0.4
Intra S America	-1.9	-1.8	-1.1	-1	-0.8	-0.8
Trans-Atlantic	-1.9	-1.7	-1.1	-1	-0.8	-0.7
Trans-Pacific	-0.9	-0.8	-0.5	-0.5	-0.4	-0.4
Europe-Asia	-1.4	-1.3	-0.8	-0.7	-0.6	-0.5

Compiled from: IATA Economics Briefing No 9: Air Travel Demand. IATA, April 2008

B. Demand Elasticities with respect to Flight Frequency

As suggested by Table 6, demand elasticities with respect to frequency variables are stable across routes- mainly on their logarithmic functional form. The estimated frequency elasticities, however, vary slightly depending on model forms. In addition, the frequency elasticities from the model indicates that for most routes adding one percent of passengers with positive distance elasticities is higher than percentage of markets with negative distance elasticities. This implies, positive distance elasticities are likely to be found in higher traffic markets, which are usually better. All being equal, while the influence of declining propensity to travel is more obvious in better served markets, the influence of mode competition is stronger in minor markets.

TABLE 6
FLIGHT FREQUENCY ON VARIOUS AIRLINES

Airline	**Frequency Elasticity**	**Remark**
ARIK	1.348	elastic
AERO	1.150	elastic
ASSOCIATED	1.212	elastic
CHANGCHANGI	1.020	elastic
DANA	1.245	elastic
IRS	0.943	inelastic
OVERLAND	1.383	elastic
AIR NIGERIA	1.064	elastic
Aggregate (panel)	1.337	elastic

Source: Authors' Compilation (2015)

C. Demand Elasticity with respect to other Variables

The income and distance elasticities are presented in Table 7. The fare elasticity is smaller than distance elasticities in absolute values (aggregate case). This indicates, the distance elasticities of low traffic markets are higher. However, income elasticities are larger, suggesting that the income elasticities of low traffic markets are higher. Flight frequency showed elastic values, fares and income (economic growth indicator) variables portrayed elastic behaviours for some airlines implying that airports, fares, flight frequencies and economic growth affect airline demand in Nigeria.

TABLE 7
FARE, INCOME AND DISTANCE ELASTICITIES OF AIRLINES IN NIGERIA

Airline	**Fare Elasticity**	**Income Elasticity**	**Distance Elasticity**
ARIK	-0.151	0.195	0.211
AERO	-0.240	0.383	0.509
ASSOCIATED	-0.097	0.766	1.459
CHANGCHANGI	-0.387	0.726	-1.066
DANA	-1.159	0.425	0.689
IRS	-0.357	0.055	0.692
OVERLAND	-0.280	1.139	0.089
AIR NIGERIA	-1.740	0.560	0.552
Aggregate (panel)	-0.319	0.193	0.924

Source: Authors' Compilation (2015)

Some studies supported the concept that demand elasticity faced by individual airline is higher than that faced by the whole market. For example, [42] estimated firm-specific elasticities in the U.S. and estimated values ranging from -1.24 to -2.34, while research works estimating market or route elasticities ranged from -0.6 to -1.6. Contrary, [6] and [36] used national-level measures of air travel in Israel and the UK respectively and produced even lower elasticity values (-0.27 and -0.7, respectively).

Several studies included income as an explanatory variable of air travel demand. This will isolate the effects of a shift along the demand curve (caused by a change in air travel fare) from the effect of a shift of the whole demand curve (caused by a change in incomes or GDP).The research works including income term all produced positive income elasticities, as would be expected (air travel increases as incomes increase). Virtually, these research works estimated income elasticities above one, generally between +1 and +2. This indicates air travel increases at a higher rate than income growth. This has important implications for policies seeking to manage air travel demand by raising the fare travel.

V. CONCLUSION

At market level, the fare elasticities from OLS estimates indicate inelastic market demand. The fare elasticities from OLS estimates are better supported by findings in the literature summarized by Gillen et al (2002)- are very wide, especially for larger absolute elasticities (smaller percentiles). For example at the market aggregated level, the elasticities of -0.062 and -0.319 were computed at Model 1 and Model 2 respectively and those from Gillen et al (2002) are -1.52 and -1.15, respectively. Although all estimated frequency coefficients indicate that potential travelers prefer routes with high flight frequency, marginal effects of different frequency variables are different. The results confirm that minimum frequency is critical to the connecting service, and thus proportional flight frequency increase on the segment with lower frequency increases service attractiveness more than equivalent change on higher frequency segment. All coefficients of scheduled flight time indicate that travelers prefer routes with shorter scheduled flight time. These values are in same order as those reported in the literature. Moreover, the elasticities calculated from the Model 1 estimates suggest that shortening one percent of scheduled flight time is expected to increase route demand by about one percent for direct routes.

The coefficient differences for on-time performance variables are statistically significant, implying, potential travelers do not weigh one-time performance of the two periods equally. [24] summarized income elasticities of market demand from empirical research works and reported quantiles are 0.81(1st quantile), 1.14 (median), and 2.05 (3rd quantile). While income elasticities from OLS estimates seem relatively low. Almost income elasticities estimates are less than 1, implying, air demand is income inelastic in most markets in Nigeria. Moreover, income elasticities have smaller variation across markets than fare and distance elasticities do. According to Model 2 estimates, in short- to medium-haul markets, distance effects reflect declining competition from competing modes, which causes air demand to increase with distance; in long-haul markets, the effect is reversed, presumably due to decreasing propensity to travel. Moreover, the estimated ratios of scale parameters from Model 2 estimates imply that a longer-haul market route attribute changes are more likely to shift traffic between routes as opposed to affecting total air market traffic.

This paper provided a short overview of domestic air-travel demand market in Nigeria. Route-based air travel demand models shows general association with the changes in demographic and economic variables. It will provide tool for short-run strategic planning for the related organizations. The trends in domestic air travel demand in Nigeria suggest that in future, private airline companies will dominate domestic market with introduction of proper level of activity, optimization of their capacity, improvement of service and operation. The results of this study will help these airlines greatly. Further research is required to incorporate international air transportation especially in light of 'Hub-Spoke' network system, which is presently popular in aviation industry.

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