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DEMAND ELASTICITIES FOR INTERCITY ROAD PASSENGER TRAVEL IN NIGERIA

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Abstract:
Elasticity examines the relative importance of causal factors. The log-linear models analyzed the revealed preference data from the period of 2014 to 2016 in 16 transport companies in Owerri. The result showed aggregate fares elasticities are low. It agrees with conventional public road transport fares elasticity value of -0.3. The estimation was smallest for distance elasticities. All frequency coefficients show that passengers prefer routes with high frequency. The coefficients of journey time portray that passengers prefer routes with shorter journey time. This paper provides a framework for the transport companies to estimate demand and to ensure business sustainability.

Key words:
Elasticity, Intercity, Road, Passenger, Transport, Demand

1. INTRODUCTION

Transport has been an integral part of man's activities in the world. “Man’s ability to move himself and his materials from one point to another on the earth significantly influence his life and his environment"[2]. [13] submitted both intra and intercity travel bridges the gap between people and resources in both space and time. Furthermore, [10] stressed on the importance of public transport in the city and its associated benefits and opined that man's basic need of food, clothing, and shelter are unrealizable without transportation. One can consider transportation to be the livewire of all socio-economic and political facets of a nation. This means that without transportation life as it were will have been bleak. There is a strong social demand for transport data that allows us to predict the future of intercity transport demand. One of the difficulties is to find the soundest predictive model. This is the subject matter of this paper

In [9] trip generation model, a linear regression approach is used due to the somewhat cumbersome formulation of a choice model for frequency choice. The composite variable that represents service characteristics is not included. Therefore, trip generation is not based on the utility maximization theory. The interrelationship between trip frequency and mode choice is not implemented in the model. Examining the elasticity of demand with respect to fuel prices can improve our understanding of the price effect, showing that rising fuel prices reduce car travel [6]. However, the value of the coefficients varies according to the model, the nature of the data and the locality [7], [8]. [3] was of the view that in public transport, that the fuel price elasticity of demand is positive. In a cursory look, the elasticity is lower than the fare disparity elasticity of demand. This has led to intellectual deduction that a decrease in fare has a great role in boosting public transport use. For the elasticity with respect to fares of transport demand is affected by mode of transport and time, the fare elasticity for buses being –0.4 in the short term and –1 in the long term. Their values for the metro were –0.3 in the short term and –0.6 in the long term [11].

Without understanding the system dynamics and more importantly, the behaviors of public travelers, it would be too difficult to make accurate forecasts, which are necessary for marketing, service planning and fare policy purposes [12], [13]. The factors influencing the public transport demand have received considerable attention in the literature but in different contexts. From the works of [1] socio-economic variables play the most important role on local public transportation. Price and time elasticities, modal choice and externalities internalization have been the leading topics in the recent literature on urban public transport demand [1]. [15] pointed out the considerable change in the travel behavior triggered mainly by socio-economic changes in the past few decades. In the words of [5] a study of this nature study provides a framework for the urban transport companies to estimate demand specifically on various routes operated and position their services by designing the service positioning matrix to ensure business sustainability.

2. METHODOLOGY

Inter-city transport market in this paper is divided into 19 origin-destination (O-D) city-pairs due to data compilation needs. Markets are specified as one directional O-D pairs originating from Owerri Urban to 19 different cities in Nigeria. Intercity travel choices include multiple products which are unique combinations of cities from Owerri. Our specification captures these important service attributes of urban transport services. Our data consist of 19 directional O-D markets and the total number of travel products on the markets filtered is 207 from 16 different transport companies with a terminal base at Owerri.

Table 1: *Urban Transport Companies Surveyed*

Transport Company	Frequency	Percent	Cumulative Percent
ABC	24	11.6	11.6
ABIA CITY	25	12.1	23.7
ABIA LINE	16	7.7	31.4
AITC	2	1.0	32.4
CHISCO	7	3.4	35.7
CONSTANTLINK	26	12.6	48.3
GOD IS GOOD	10	4.8	53.1
GUO	46	22.2	75.4
HEARTLAND EXPRESS	3	1.4	76.8
IMO EXPRESS	2	1.0	77.8
ITC	11	5.3	83.1
LIBRA	2	1.0	84.1
MULTILINE	2	1.0	85.0
PMT	13	6.3	91.3
TRACAS	15	7.2	98.6
YOUNGS	3	1.4	100.0
TOTAL	207	100.0	

Source: Fieldwork

After the data were filtered based on the criterion of retaining routes with at least 2 daily trip frequency, 207 daily route observations to were used estimate the model. If the prospective passengers are of the same characteristics (μ_{irt} = 0), outside the stochastic terms ε_{irt}, the equations to estimate the determinants of demand of inter-city passenger traffic in Owerri bus terminals within the period under study are as follows:

We specify the following models for estimation in logarithmic form:

Model 1:

$$In^{D}{}_{\text{topax}} = \beta_1\, InFreq + \beta_2\, InFare + \beta_3\, Dist + \beta_4\, InJtim + \varepsilon irt.......(1)$$

Model 2:

$$In^{D}{}_{\text{pax - km}} = \beta 1\, InFreq + \beta_2\, InFare + \beta_3 Jtim + \beta_4\, InVcap + \varepsilon irt....(2)$$

The explanatory variables are defined as follows:

Freq= represents the frequency of trips at route r;
Fare= available bus fare of route r, which is the same for all routes of the O-D city pair at time t served by the same transport company;
Jtim= journey-time performance of vehicle of a respective transport company
Dist = distance between origin and destination
Vcap = vehicular capacity
$\mathbf{D}_{\textit{totpax}}$= demand expressed as total number of passengers
$\mathbf{D}_{\textit{pax-km}}$ = demand expressed as passenger kilometer

This research estimates the aggregate demand forms for the total number of passengers carried per day, and also estimates the aggregate demand model for another demand proxy (passenger-kilometer done per day) for comparisons. Routes are categorized in a city-pair by assuming that the routes with more similar journey time and fare rates are more likely to be competitors. The results of the estimation of the models are shown in Tables 2-4. The log-linear model employing passenger-kilometres is the preferred model for two reasons. First, the Model 2 model confirms the non-homogeneous correlations among alternatives, implying that the model have unreasonable substitution patterns among alternatives. Second, the OLS estimates infer more sensible demand elasticities, and correlations of total utilities for alternatives than those of direct linear modelling method [5].

Table 2: *Data Estimation Results for Aggregate Inter-city Travel Demand*

Variable	**Model 1**	**Model 2**
Frequency (trips per day)	1.222*** [0.064]	1.266*** [0.476]
Journey Time (minutes)	-0.380** [0.137]	-.206*** [0.110]
Fare (in Naira)	- 0.236*** [0.063]	- 0.285*** [0.043]
Vehicle Capacity		0.165* [0.083]
Route Distance (kilometres)	0.083 [0.083]	
Constant	1.127** [0.406]	1.590*** [0.476]
R^2	*0.668*	*0.817*
Adjusted R^2	*0.858*	*0.811*
F	*67.386*	*149.381*

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.

Source: Authors' Computation from SPSS

Table 3: *Data Estimation Results for Aggregate Intercity travel Demand (Short Distance)*

Variable	Model 2
Frequency (trips per day)	1.266*** [0.476]
Journey Time (minutes)	-1.206*** [0.110]
Fare (in Naira)	-0.285*** [0.0]
Vehicle Capacity	0.165* [0.083]
Constant	1.851* [0.885]
R^2	*0.691*
Adjusted R^2	*0.667*
F	*28.233*

1. **Model 2**: Dependent variable = In (Passenger-Kilometres);
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.

Source: Authors' Computation from SPSS

Table 4: *Data Estimation Results for Aggregate Intercity travel Demand (Long Distance)*

Variable	Model 2
Frequency (trips per day)	1.247*** [0.084]
Journey Time (minutes)	-1.244*** [0.220]
Fare (in Naira)	-0.357 [0.260]
Vehicle Capacity	0.111 [0.096]
Constant	1.3493** [1.447]
R^2	*0.676*
Adjusted R^2	*0.664*
F	*55.465*

1. Model 2: Dependent variable = In (Passenger-Kilometres);
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.

Source: Authors' Computation from SPSS

3. RESULTS AND DISCUSSIONS

The paper presents the elasticity estimates (the beta-values of the structured equation model) of selected bus companies in Imo State. In addition, the estimated elasticity with respect to fare is compared with those in the literature. The elasticity of demand with respect to a service variable is determined by calculating the change in demand resulting from an increase in the variable by a percentage, all things been equal. This model is used to find route-based demand elasticities with respect to fare, frequency, vehicle capacity, route distance and journey time. The asterisk * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$ represent the levels of significance of the parameter estimates.

3.1 Demand Elasticity with respect to Fare

Fare elasticities of route demand are summarized in Table 5. Since prospective passengers have more choices at the route, fare elasticities of route demand are expected to be larger (in absolute values). While the fare elasticities calculated from OLS (ordinary least squares) estimates are consistent with the expectation. In addition, when market size (measured by the number of passengers) is taken into account, the elasticities become smaller in terms of actual values. Details of these elasticities are summarized by aggregation in Table 5.

Table 5: *Fare Elasticity of Demand*

Scenario	Fare Elasticity	Remark
Short Distance	-0.285	inelastic
Long Distance	-0.357	inelastic
Aggregate	-0.285	inelastic

Source: Authors' Computation from SPSS

Fares are crucial to the operation of public transport since they form a major source of income to the stakeholders. Increase in fare will result to a proportionate decrease in patronage. In both the short and long distance journeys, there were inelastic, hence increase in fares will not affect level of patronage.

Fare elasticities are not static, it changes over time for a given period as a result of fare changes. Therefore it is increasingly common for analysts to distinguish between short distance and long distance-run elasticity values. Fare elasticity is affected by transport mode, and the time and space dimensions of the operation. In the paper, values of elasticity from other researches are studied to provide a current information of fares elasticities and its relationship with other variables. The results of this analysis are shown in Table 6. It can be seen in a broad dimension that bus fare elasticity ranges from -0.3 in the short distance and -0.4 in the long distance. This can be confirmed from [4]

Table 6: *Comparison of Fare Elasticity of intercity travel demand with literature*

Scenario	Fare Elasticity from this paper	Elasticity from literature [7]
Short Distance	-0.285	-0.30
Long Distance	-0.357	-0.40

Source: Authors' Computation from SPSS

This analysis concludes that fares elasticities are low so that increases in fare will almost always result to increases in revenue. The analysis resulted in the conventional public road transport fares elasticity value of -0.3. The fare elasticities from the OLS estimates indicate inelastic market demand in conformity to other studies. This shows that fare elasticities of long-distance traffic markets are higher than those of short distance traffic markets. A possible reason is that fares in the long distance traffic markets are relatively high. Thus, a fare increase reduces more service attractiveness in these long distant markets.

3.2 Demand Elasticities with respect to Frequency

Demand elasticities with respect to frequency variables are consistent across routes-mainly due to their logarithmic transformations. The estimated frequency elasticities are slightly varied due to model forms. Passengers have a higher propensity to travel on routes with greater frequencies due to regularity of vehicle schedule on those routes.

Table 7: *Frequency Elasticity of inter-city travel demand*

Scenario	Frequency Elasticity	Remark
Short Distance	1.266	elastic
Long Distance	1.247	elastic
Aggregate	1.266	elastic

Source: Authors' Computation from SPSS

3.3 Demand Elasticity with respect to other Variables

The journey time and vehicle capacity elasticities are presented in Table 8. The vehicle capacity elasticity is smaller than the journey time elasticities in absolute values (aggregate case). This indicates that the journey time elasticities of low traffic markets are higher.

Table 8: *Other elasticities of inter-city travel demand*

Variable	Elasticity	Remark
Journey time	-1.206	elastic
Vehicle Capacity	0.165	inelastic

Source: Authors' Computation from SPSS

However, the elasticity with respect to journey time is elastic with the expected sign. Hence passengers in inter-city journey are more critical towards journey time and may opt out for an alternative mode of travel when the journey time of the road transport companies are increasing due to road conditions or other variables. In addition, passengers are not responsive to vehicle capacity. They are more interested in having a safe and reliable journey. The prevalent public transport modes in Nigeria are the small capacity vehicles which offer a more flexible level of services.

4. CONCLUSIONS

The distributions of the fare elasticities clearly show that estimation method (OLS) create much larger differences of fare elasticities than the direct liner model form do. At a market level, the fare elasticities from the OLS estimates indicate inelastic market demand. This analysis led to the conclusion that overall fares elasticities are low so that increases in fare levels will almost always lead to increases in revenue. The analysis led to the conventional public road transport fares elasticity value of -0.3 [3]. All estimated frequency coefficients indicate that prospective passengers prefer routes with high flight frequency. The vehicle capacity elasticity is smaller than the journey time elasticities in absolute values (aggregate case). This indicates that the journey time elasticities of low traffic markets are higher.

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