ESTIMATION OF INTER-CITY TRAVEL DEMAND FOR PUBLIC ROAD TRANSPORT FROM OWERRI TO SOME SELECTED CITIES IN NIGERIA

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CERTIFICATION

This is to certify that this work **"Estimation of Inter-City Travel Demand For Public Road Transport From Owerri To Some Selected cities In Nigeria"** was carried out by ERUMAKA, ONYINYECHI (Reg No. 20124763058) in partial fulfillment for the award of the Master of Science Degree (M.Sc) in Transport Management Technology of the Federal University of Technology, Owerri, Imo State, Nigeria.

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DEDICATION

This work is dedicated to the Almighty God who has been faithful to my life and also to my wonderful husband Prof. E. N. Erumaka and our son Emmanuel Erumaka for supporting and being there for me.

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ABSTRACT

This study calibrates an intercity travel demand model which uses the principal structural variables that have been identified in the literature. It uses a robust econometric method which has been little applied in the sphere of land transport in Nigeria. This research develops an urban public travel demand model for 19 directional O-D city-pair network originating from Owerri Urban. Using revealed preference data from the period of 2014 to 2016 which was filtered into 207 observations operated by the 16 transport companies in Owerri, Imo State. The analysis modelled the pattern of correlations among service variables which are fares, journey time, distance, frequency by a log-linear model using OLS and Logit estimation. The estimates yield better demand elasticities than those of direct linear models. Other findings include that; overall fares elasticities are low, so that increases in fare will almost always lead to increases in revenue thus decreasing in the number of passengers. The result of the analysis agrees with the accepted 'standard' public transport fares elasticity value of -0.3. Demand elasticities with respect to Frequency are positive and with respect to Fares are negative. All estimated frequency coefficients indicate that potential travelers prefer routes with high frequency. The coefficients of journey time indicate that travelers prefer routes with shorter journey time. Whereas no specific time trends for frequency and fare effects are found, no structural changes related to other variables exist. There are significant differences between the factors associated with short-distance and the factors associated with long-distance urban travel behavior. This 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.

CHAPTER ONE

INTRODUCTION

1.1 Background to the Study

Transport has been important component of man's activities in space."Man'sability to move himself and his materials from one point to another on the earth significantly influences his life and his environment" Ahmed (2013). Tolley and Turton (1995) submitted both intra and intercity transportation system bridges the gap between people and resources in both space and time. Furthermore, one of the ways by which man organizes the space around him is through formation of settlement and the use of transportation as a tool to bringing orderliness into the settlement .Furthermore, Ogunsanya (2002) emphasized on the inevitability of transportation in the city and related basic necessities of life, and stressed that man's basic need of food, clothing and shelter could be hardly achieved without transportation. One can consider transportation to be the life of all socio-economic and political life of a nation. This means that without transportation life as it is today would be inconceivable. World Bank Review (2012) echoed the same point by stressing that economically, transport is the blood of cities in; most countries, including developing countries, cities are the major source of the national economic growth. The World Bank publication (2012) further asserted that socially, transport is the means of (and the lack of transport is the impediment to) accessibility of jobs, health, education and social services that are essential to the welfare of the people. There is strong social demand for data that allows us to foresee the future and prepare for it as well as possible. This expectation is becoming stronger and stronger as environmental concerns become more alarming. Transportation does not escape from this rule. Having an idea, for example, of the order of magnitude of intercity travel would help us understand what tomorrow's cities may be like. One of the difficulties is to find the most appropriate forecasting model. This is the subject covered in this study.

The estimation of long-term travel demand requires specific modeling which identifies the structural factors of travel. One of the first such factors to be identified was the quantity of goods or services available, be it in private cars (Mogridge, 1967 and 1989; Evans, 1970; Jansson, 1989; Button, Ngoe and Hine,1993; Gakenheimer, 1999; Ortuzar and Willumsen, 2006; Holmgren, 2007) or in public transportation (Wardman, 2004; Bresson, Dargay, Madre and Pirotte. 2003,2004; Garcia-Ferrer, Bujosa, DeJuan and Poncela. (2006).

The literature shows that other structural determinants are also considered, for example the user cost of a trip (McFadden, 1974; Paulley, Balcombe, Mackett, Titheridge, and Presto. (2006), the income of the household that travels, (Schafer and Victor, 2000; Dargay and Hanly, 2002; Medlock and Soligo, 2002) or the spatial distribution of transportation (Kain and Fauth, 1977; Oum, Waters 11, and Young. 1992; Giuliano and Dargay, 2006; Davidson, Donnelly, Vovsha and Freedman; 2007). Moreover, in addition to these structural factors, travel differences between different groups of countries also seem to play a role (Schafer and Victor, 2000; van de Coevering and Schwanen, 2006).

This study describes a demand model based on these structural factors. We have to verify that they are statistically significant and checked whether they have a similar impact on intercity travel in different groups or countries. We have used a robust econometric method (2SLS, SUR, 3SLS2, Chow's stability test, see Greene, 1993; Maddala, 2008) which has, to the best of our knowledge, only occasionally been used in the sphere of transport (apart from by Cerver and Hansen, 2002; Zhou and Kockelman, 2008). We have to check whether our findings agree with those in the literature. Previous study results show that two variables stand out from the others: the user cost of trips (by private car and public transport) and urban density. It is these explanatory variables which stand as the best to the various econometric tests which previous studies applied. The value of the elasticity coefficients, moreover, should concur with those in the literature. Furthermore, the estimated demand functions for a given country seem to be independent of the group of countries to which it belongs. This may seem surprising but it can be explained by our inability to take account of urban GDP in a satisfactory manner.

The inter-city urban transport challenge in Nigeria has been posed in this study as one responsible for rapidly growing mass mobility needs, within a context of increasingly constrained resources. We focus on public transit because a significant proportion of trips in the large urban areas are conducted by this mode, and indeed, the poor majority depend on it for their economic survival. And with rapidly growing urban populations, many of whom will likely be poor, the provision of affordable and convenient public transit will continue to be of vital importance for many years to come.

While maintaining and expanding transit provision would be desirable from the perspective of catering for the mobility needs of the majority of the urban population, and curbing personal motor vehicle activity and its various associated impacts, doing so will not be easy. The supply situation, as a result of which transit is ever more unreliable, crowded, inconvenient and time-consuming, is aggravated by an ageing bus fleet, shortened vehicle life due to heavy use, poor fleet maintenance, and poor roads (Agunloye, 2011).

As a response to the serious shortcomings of the public bus transport system, most cities in Nigeria have turned increasingly to the private sector to help expand intercity travel service since the early 1990s. In this regard, it is worth noting that a large number of private operators run the majority of Nigeria buses, under conditions of high capital costs, unregulated fares, and extremely slight margins. The operators therefore have little ability or incentive to properly maintain their vehicles for passenger comfort and convenience, let alone invest in fleet expansion or improvements (Agunloye, 2011).

Kenworthy and Laube (1999), for example, argue strongly in favour of urban rail, because of its potential to transport large numbers of people quickly, reliably, comfortably, and safely, and to attract people from personal motor vehicles in addition to captive users. They point to Hong Kong, Singapore and Tokyo, which, despite their wealth, have low automobile dependence and high transit usage, in large part due to investment in rail transit. Mohan (1997) have assessed urban rail with specific reference to low-income countries, based on a survey of the performance of rail systems constructed over the past 25 years in several cities in these countries. Most systems, with some notable exceptions, such as Hong Kong and Singapore, have experienced construction delays, high capital costs (ranging from US$ 8 million to US$ 165 million per kilometre), lower than expected patronage levels and revenue-to-operating cost ratios, and massive continuing subsidies. For all this, there appears to be only short-lived or no impact on congestion in the majority of cities for which information exists, because private traffic rapidly grows to utilize released road capacity. While rail systems may cause bus users to transfer to them, they attract no more than a small share of private motor vehicle users (which is key in terms of reducing congestion and emissions). Furthermore, while passengers are mostly captured from buses, reduction in bus traffic is not proportional, and in any case represents only a small portion of overall vehicle traffic (Mohan et al 1997; Sathaye et al 1994).

The financial viability of urban rail systems depends critically on a large population with a high per capita income, high utilization levels and fares, and low staffing and wage levels. Experience from several low-income country cities suggests that high fares cannot be charged without losing patronage. To attract patronage, the integrated bus and rail fare should ideally not be much higher than the existing bus fare; if it is, the poor will continue to use buses. And any attempt to remove bus competition will likely cause major disruptions in peoples' lives, and the displacement of many small operators (Mohan et al 1997). All of this means that fares in low-income cities are likely have to be subsidized, with adverse implications for financial viability. Another important issue is the inability, because of constrained resources, to build a rail system that is both extensive and fine-grained, which would ideally be required to make a significant dent in personal motor vehicle use in urban areas that are growing rapidly in all directions.

Given the foregoing, and the needs, capabilities and constraints in the Nigerian context, more efficient use of existing transit along with road infrastructure is called for. This would indicate, first of all, the need to improve service with the existing transit fleet, which is by no means an easy task, given the various transit-related difficulties in the Nigerian environment. The public transit challenge in Nigerian cities may succinctly be described as one of improving service to maintain and enhance ridership, at low cost, in dense settings with limited road capacity. One possible answer to this difficult challenge is to implement, wherever appropriate and possible, rapid bus transit systems operating on dedicated busways, perhaps with low-floor buses, since such systems offer high line-haul capacities, at significantly lower costs than urban rail (Rabinovitch and Leitman 1996; Mohan et al 1997). This is in operation in Lagos BRT.

The question is, what will the infrastructure needs be for dedicated busways, how can they be accommodated in dense settings, and to what extent if at all can the existing road infrastructure be made use of for this purpose? We have already discussed how these modes are forced to share road space with fast moving motor vehicle traffic, and his not only increases hazards for non-motorized users but also causes the existing transport infrastructure to be used inefficiently and all other modes to operate sub-optimally, including severely hampering bus operation and service provision. The net result is that while all modes are adversely affected, the most environmentally and socially friendly modes, and the vast majority that depends on them, suffer the most.

Much higher levels of service and higher traffic flows can potentially be achieved with the existing infrastructure, provided it is used efficiently, especially in cities, with adequate road space. It is important that infrastructure be designed to accommodate multiple modes, based on the recognition that, just as dedicated facilities for non-motorized modes are necessary to make the use of these modes attractive, bus systems need to be separated from slow moving non-motorized modes in order to be able to operate efficiently.

Given the imperatives and realities in the Nigerian context and the Lagos experiment, strategies such as this that will be required to meet mass mobility needs over the coming decades, and to build urban access and mobility systems that are low cost, resource conserving, environmentally benign and socially just.

1.2 Statement of the Problem

The problems facing the urban centers are not only many but are also very complex; one of the most apparent, being intra-town mobility. Intra-City transportation problems in Nigeria could include traffic congestion, poor road facilities, poor environmental condition, road degradation, insufficient right of way, air and environmental pollution. The problem with linkages within urban areas has existed for a long time and so most cities in Nigeria have been known for its massive traffic congestion worldwide. Suggesting that the traffic management apparatus is not efficient and effective and it indirectly contributes to the problems rather than solving them. Consequently prompting the need to find out what is actually wrong.

Knowledge of travel demand for public transport service is the key to a successful system transformation. There are conscious efforts by the planners in Nigerian road transport industry to expand capacity of the road space. While overestimating future traffic leads to overinvestment, underestimating future traffic distorts system operations and causes traffic congestion, thereby increasing transport costs which means that a better understanding of intercity travel demand will make the expansion more cost-effective and beneficial to the to the society. This is presently lacking suggesting that there are problems that need to be identified.

Current understanding of the demand for public transport service fails to address several significant questions: (1) what is the relative importance of causal factors (such as, trip frequency, route distance, journey time, and fare) in determining demand among routes? (2) How have these relationships changed over time? Appropriately identifying causal factors and quantifying their effects contribute to the fundamental understanding of intercity travel demand and allow sensible predictions of demand response to a wide range of future scenarios, including different levels of congestion, network connectivity, vehicle size and frequency, and fuel price, among other factors. Existing models in Nigeria are not sufficient to meet these purposes hence the need to estimate the inter-city travel demand for public road transport in Nigeria.

Most existing models in the literature only deal with geo-economic considerations, or treat these two phenomena sequentially. The sequential approach is inappropriate since it implicitly assumes that the total demand volume is independent of alternative cost and service quality. In addition, studies in intercity travel demand literature usually include cost and flight frequency as causal factors, other factors- such as journey time and capacity- are seldom investigated (Camagni, Gibelli and Rigamonti, 2002). Specifying these additional causal factors not only allows predictions of demand response to changes in these factors, but also affects the estimated effects of cost and frequency of trip.

The travelling public face a rich array of travel alternatives, from whether to travel, to what transport company to use. Some alternatives are very similar to each other while others are quite different. In the formulation of random utility theory similarity between alternatives is captured by the correlations between their stochastic utilities: if an individual that is predisposed toward alternative X is also likely to be predisposed toward alternative Y, we consider X and Y to be correlated. We seek to understand the pattern of such correlation evidenced in the distribution of traffic among routes (including the "null route"). Such patterns are of inherent interest, and must be properly represented in order to accurately estimate effects of causal factors, and are critical in predicting how demand will respond to changes in service supply.

In summary, intercity travel demand models in Nigeria and literature have shortcomings in terms of quantification of their variables which this research seeks to address. In so doing we contribute to both fundamental understanding of travel demand especially in Nigeria and the practical need to predict how demand will respond to a range of future scenarios. It is in light of this that this study seeks to estimate intercity travel demand with a view to identifying and modelling key determinants of public transport behaviours in the study area.

1.3 Aim and Objectives of the Study

The aim of this study is to build travel demand models for public transport in Nigeria that can be used by passengers and operators to evaluate the overall travel demand. To achieve the main objective, the following specific objectives are addressed:

1. To identify key variables influencing the choice of inter-city public transport in Nigeria;
2. To determine what extent these variables influence the demand for public transport;
3. To assess the relationship between change in service characteristics and demand.
4. To assess the structural relationship between public transport service variables.

1.4 Research Questions

To address the aim of the study, the following questions came to mind;

1. How does fares, journey distance, frequency of trip and travel time affect demand for intercity transport demand?
2. How is public transport demand affected by service characteristics?

3. Has the structure of public transport demand in the road transport sector changed over time?
4. What is the structure of relationship of public transport service variables?

1.5 Statement of Hypotheses

H_{01}: Service variables that impact on inter-city intercity travel demand are not correlated

H_{02}: The causal factors are not critical to inter-city intercity travel service demand in Nigeria.

H_{03}: The structure of public transport demand in Nigeria has not changed over time.

H_{04}: There is no defined structural interrelationship among public transport service variables in Nigeria.

1.6 Significance of the Study

One of the possible solutions to handling the anomalies in city transport is the preference of public transport. Consequently, it is important to plan and operate a high level public transport service. The bottleneck of the planning of such systems is the knowledge of user demand. Without this knowledge, even the smallest change in the system is only a guess work, and the effect is unpredictable. The cognition's methods of travel demand have been known for a long time, but their use hasn't been explored. Through our research we shall build a model which is able to generate a travel demand model for inter-city public transport with the use of the present transport system's characteristics in Nigeria. This research is significant because it advances the disaggregation of variables of public transport movement.

1.7 Scope of the Study

The results of this study are distillation and synthesis of identified published and unpublished evidence on the influencing factors drawn from three key areas; which include fundamental principles relating to public transport demand; evidence from research carried out by other researchers in the world and empirical results for a range of modes.

1.8 Limitation of the Study

The data for the study mainly came from existing studies and literature identified through searches for relevant literature in publication databases, materials supplied by public transport operators and contacts with analysts in the field. Most findings reviewed relate to the intercity market with little references to rural areas. The inter-city long-distance and short distant market are covered, and hence 'long' distances refer to distances above 30 kilometr

CHAPTER TWO

LITERATURE REVIEW

2.1 Conceptual Framework

Intercity travel is the travel between cities or other points of interest that are separated by some significant distance. The transportation literature generally refers to long-distance travel as intercity travel. The term long-distance travel is defined as trips of a certain minimum distance. However, the thresholds for long distance travel in various countries are different. All these values are derived by population surveys. The thresholds can vary from 50 miles (UK) to 100 miles (USA) (Limtanakool, Dijst and Lanzendorf, 2003). Even within the USA, there exists a plethora of definitions (US DOC, undated). In this study, 100 miles is used to define intercity travel, regardless of any overnight stay.

Intercity travel behavior is different from urban travel behavior in certain aspects, such as travel frequency. However, it still follows the general four-step model for urban travel behavior: trip generation, trip distribution, mode choice, and trip assignment. Intercity travel decision making is typically assumed to consist of trip generation, destination choice, mode choice, and route choice.

Conventional travel demand models separate the demand functions into four steps. When used for intercity travel, the model consists of two sequential steps that predict intercity travel by mode (Koppelman and Hirsh, 1984). The first step forecasts the total intercity travel volume for city pairs. The second step distributes the volume via a logit model. Typically, the number of trips is formulated as a function of the socioeconomic characteristics of city pairs and composite measures of the level of service. Today these models are still in applications such as forecasting high-speed rail ridership (Brand, Parody, Hsu, and Tierney, 1992). These models provide some insight into intercity travel behavior. However, the model obscures much of the information in the data. Its behavioral implication that individuals decide their travel behavior in stages does not appear to be consistent with reality. Hence, it has limitations as an estimator of intercity travel demand (Peers and Bevilacqua, 1976).

2.1.1 Trip Generation/Frequency Models

Trip generation is defined as the number of individual trips generated in a given period of time. Traditionally, in travel demand modeling, trip generation is the first component that provides the possibility for the next steps, such as destination choice and mode choice. In the context of urban travel, a trip can be home-based or non-home-based. In practice, according to Ortuzar (1994), it is also classified by purpose, such as trips to work, trips to school or college, shopping trips, social and recreational trips and other trips. Alternatively, the trips can be classified by person type based on income level, car ownership, household size and structure, which is often used as the model segmentation base. In an intercity travel context, a trip is usually categorized as a business trip or nonbusiness trip. It also can be further classified as business, combined business/pleasure, convention, conference or seminar, visiting relative or friends, rest or relaxation (the 1995 American Travel Survey). Trip generation analysis requires identification of the factors that affect trip generation. Often, the variables taken into account are characteristics of the traveler, and personal trip attraction (Ortuzar, 1994), as well as the attributes of alternatives. The characteristics of travelers include household income, car ownership, household structure, and household size. The personal trip attraction factors include the destination's socioeconomic, industrial, or residential context. The performance of the available alternatives may influence the number of trips, particularly for intercity non-business trips. For instance, reduction in travel time or cost may induce more frequent trips. The opposite may reduce trip frequency or consolidate trips. The effects of changes in modal attributes on travel frequencies may also exert effects on choice of mode for some trip purposes as stated by Domencich and McFadden (1995). The early trip generation models, based on aggregate data, predicted total trips between city pairs (ITE, 1992). The modeling methods generally include regression models, cross-classification analysis, or a combination of both. These methods still have applications due to their mathematical feasibility, data availability, and ease of interpretation (USDOT, 1999). Disaggregate trip generation models were developed to be consistent with other components of the transportation demand modeling system, such as mode choice models and destination choice models. These models are based on individual level data. Trip generation was assumed to be a process of choosing one option from the following alternatives: making no trip, one trip, two trips and so on. Therefore, these models predict the probability of an individual making a certain number of trips within a given period. The detailed progression of the disaggregate trip generation models is presented below. As early as 1970, Stopher and Lisco suggested the logit model for trip generation.

Subsequently, Talvitie (1973) proposed a disaggregate trip generation model, at only a conceptual level. Charles River Associates (CRA) (Domencich and McFadden, 1995) developed a binary logit model to determine the probability of an individual undertaking a shopping trip on a given day. In this model, the inclusive price, which is defined as a weighted average price over all possible destinations, was used as an independent variable. Another attempt to improve the trip generation model was carried out by CRA (Tye et al., 1982) which provided no significant improvement since it simply utilized different independent variables, such as the number of licensed drivers minus number of workers in the household.

However, it was stated that application of the logit model to this choice set would create a problem due to the logit model's basic assumption of Independence of Irrelevant Alternative (IIA). This assumption states that the relative probability of each pair of alternatives is only related to the characteristics of this pair of alternates and independent of the presence or characteristics of all other alternatives. Lastly, the authors concluded that the "HA property of the MNL appears to be a fatal defect in its use for trip generation". The use of choice theories for improving the explanatory power of trip generation models was tested by Tardiff (1977). A linear regression model and two variations of logit models were compared. One of the models was a binary logit model, in which one option is larger-than-thirteen trips per 28 days; another option is less-than thirteen trips. Another logit model examined was the linearized form. It forecasts the share of households that undertake a certain number of trips. The calibration results showed that the linear regression model was better in performance than the logit models. However, the regression model is not based on choice theory but rather on the hypothesis that those households with larger sizes, and/or more resources to travel, will make more trips. A trip generation model consistent with choice theory and similar to the mode choice model would be more plausible. Sheffi (1979) developed an ordered logit trip generation model. The choice set of alternatives is trip frequencies of zero, one trip, two trips, and so on. These choices are known as rank ordered, or nested choices. This model performed well in predicting behavior. In this model, a particular alternative, i.e. two trips, implies that all lower ranked alternatives (of making the first trip) have to be chosen. It is assumed that decision-makers choose the options step by step. Another property of this model is that binary logit is used, which means that it does not have the IIA problem. For estimation, there are two types of approaches. One of them is step-by-step, which applies the binary logit estimation at least "n-1" times if the largest number of trips is "n". The other one is the simultaneous maximization likelihood method. This estimation method combines all the steps into one likelihood function. The cost of estimation by a step-by-step approach could be high as a result of the need to estimate binary logit models "n-1" times. The estimated coefficients for the same variables in different binary logit steps may not be the same. This is not consistent with travel behavior. Thus, the simultaneous estimation method is favored. Vickerman and Barmby (1985) employed this ordered logit model to estimate shopping trip frequency in England. The results indicated that the model was favorable with regard to the applicability of this model. The most recent application was Damodaran (1988) who combined this model with mode choice.

2.1.2 Early Intercity Travel Demand Models

As early as 1961, Lansing et al. applied simple gravity models for New York and Chicago. The initial gravity model described the relationship between the total traffic between each of these two cities and the demographic and socioeconomic characteristics of the city pairs. In this model, only population, per capita income, and distance were included as independent variables. In 1969, Quandt and Young improved the initial model. Later, it was employed in the Northeast Corridor Project to forecast the ridership on potential and existing modes of intercity travel along the Washington DC - New York - Boston corridor (U.S. DOT, 1970).

Another type of early intercity travel demand model was the direct demand model. This model combined trip generation, trip distribution between cities, and modal choice in a single demand equation. The data used for these models are observational data on geographic aggregates. Most of the direct travel demand models were developed in connection with the Northeast Corridor Project. Of most interest are the Kraft-SARC model (Kraft, 1963), the Quandt-Baumol abstract mode model (Quant and Baumol, 1966), and the Blackburn model (Blackburn, 1970). The number of observed round trips by purpose and by mode between zonal (or city) pairs is used in this class of models as the units of observation. Hence, it circumvents the trip distribution and separate modal split problems.

Meyer (1971) showed that the Kraft-SARC Model is, in its implicit form, an example of a direct and specific model. The Kraft-SARC Model is as follows:

$$T_{ijm} = \beta_{mo} \prod_{r}^{R} A_{ijr}^{Bmr} \prod_{n}^{m} \prod_{s}^{S} C_{ijns}^{\alpha_{mns}}, (m = 1,2,\ldots,M)$$

T_{ijm}: Travel demand between I and j and by mode m,

A_{ijr}: Observations on the r^{th} socioeconomics activity variable for $(I,j)^{th}$ city pair and

C_{ijms}: Observation on the s^{th} generalized cost variable (including level of service or the impedance variable) for mode m from I to j.

Involved here are R socioeconomic activity variables for the city pair, and s generalized cost variables of mode m.

The Kraft-SARC model implies the presence of cross elasticity among modes. The model includes travel time and travel cost by all modes available in the city pair. Because of this, it is more applicable to intercity travel analysis than the Quandt-Baumol abstract mode model, which is formulated as follows:

$$\log RPM_i = \alpha_0 + \alpha_1 \log X + \alpha_2 \log F + \alpha_3 \log(F_i/F) + \alpha_4 \log S + \alpha_5 \log(S_i/S) + \alpha_6 \log D + \alpha_7 \log(D_i/D) + E.$$

Where:

RPM The number of revenue passenger miles carried on mode i,

X: The number of characteristics of the city pairs that influence demand but of no concern here,

F: The mode with lowest fare,

F_i/*F:* The relative fare of mode i,

S: The speed of the fastest mode,

Si /S): The relative speed of mode i,

D: The departure schedule of the most frequent mode, and

Di /D: The relative schedule of mode i.

Here, the Revenue Passenger Miles (RPM) are related to characteristics of the city pairs, the lowest fare of all modes, the speed of the fastest mode, and the departure schedule of the most frequent mode. In the Quandt-Baumol abstract mode model, the travel characteristics of the best mode, in terms of the lowest fare, the highest speed and the most frequent schedule, determine the volume of travel between city pairs. A more detailed review of the model can be found in Lave (1972).

Blackburn (1970) model proposed an individual choice model for determining alternative modes of traveling and alternative number of trips. The individual can have any number of trips within the study periods. The model was derived from utility maximization theory, which is also the foundation of this dissertation. The model aggregates demand over individual demand functions to get an aggregate model of passenger demand. It is assumed that modes, characterized in terms of inclusive prices, are perfect substitutes so that the individual always selects the cheapest mode. Most of Blackburn's analytical efforts are then devoted to aggregate demand from the demand of individuals. An additional model is the multistage sequential model developed by McLynn and Woronka (1969). This model involves two stages: a combined trip generation distribution stage and a mode split stage. Rice et al. (1981) have shown mathematically that there was no difference between the direct and two-stage models and that one could be derived from the other.

2.1.3 Simultaneous Travel Demand Models

For some time, the sequential four-step model has been employed. Mainly, this is due to the fact that it is easy to implement in practice. However, the sequential method is not consistent with the individual's decision-making process, since decisions of whether to make a trip, the destination, and the travel mode are seldom undertaken by an individual in stages. Therefore, a simultaneous model is becoming more widely used. Early simultaneous models were either aggregate or disaggregate. Basically, the aggregate simultaneous model incorporates feedback into the four-step travel forecasting procedure. It results in a combination of trip distribution, modal split, and traffic assignment (Boyce and Zhang, 1997; Tatineni, 1992). The other aggregate simultaneous model is an equilibration procedure which provides a simultaneous solution to the trip generation, distribution, modal split, and assignment problems (Safwat and Magnanti, 1988). This modeling approach was applied to intercity transportation planning in Egypt (Moavenzaden, Markow, Brademeyer and Safwat, 1983; Safwat, 1987). In these studies, it was concluded that the approach was able to predict rational behavioral responses of users to policy specifications. Since the disaggregate approach is adopted in this study, the following review is confined to the disaggregate model. The first disaggregate simultaneous model estimates the combined probability of destination and mode choices within a joint logit model (Ben-Akiva, 1974). This model can estimate the joint probability that an individual will take a trip to a certain destination by a particular mode. Under such a structure, the choice set contains all combinations of destinations and modes that are feasible for an individual. The multinomial logit model (MNL) was used to estimate the choice probability. However, the joint model may violate the IIA assumption. This violation can be avoided by the use of a nested logit model. This model was first proposed by Ben-Akiva (1974) and has been applied subsequently by others, such as Sobel (1980). The simultaneous mode and destination choice model by Ben-Akiva derived the combined probability by assuming that the distribution of error terms is type I extreme value. In this nested logit model, it is easy for the choice set to contain all feasible combinations of destinations and modes. One estimation method for this model is full information estimation. This leads to the simultaneous model between the mode choice and destination choice. The probability also can be written as a product of conditional and marginal probabilities that represent different decision sequences. However, the parameters were sensitive to the structure used. It was suggested that the simultaneous structure is preferred since there were a priori reasons to accept it. Later in 1976, Adler and Ben-Akiva extended the nested logit model to include trip generation in addition to destination and mode choice. However, the trip frequency was restricted to zero or one. It did not address the problem of a large choice set resulting from all possible combinations of trip frequency, mode, and destination. The following are some recent models that are similar to this study.

2.1.4 Charles River Associates (CRA) Model for Travel Demand

Domencich and McFadden (1996) developed a model for urban travel demand analysis that is close to the direct demand model. This study examined the number of directed round trips between any zonal pair for a given purpose and mode as a function of the number of individuals and socioeconomic factors, the appropriate measure of level of 19 activity, and other relevant characteristics, as well as the travel times and costs of alternatives. The individual components of the model are "interrelated" through the attributes of the trip - time and cost variables - so that the separate components link together in an overall demand model. The distilling of information on attributes across a broad, though discrete, set of choice alternatives into a single "index of desirability" or inclusive price of travel is the success of the nested logit model. Obviously, the model is not completely interrelated because the utility is assumed to be separable. Different components are estimated separately, although they share the same variables: inclusive cost. Also, it only considers the choice between no trip and one trip due to limitations in the study case. The model's permitted shopping trip frequency allows just one or zero shopping trips per household per day, which may be limited for many applications.

2.2 Theoritical Frame Work for Modelling Travel Demand

In principle, the quality influences the consumers' satisfaction. In urban transport, apart from the users' satisfaction, the mobility system must also satisfy the political objectives, particularly the increase in the market share of public transport, release of budget means and environmental protection. Therefore, urban public transport planning is the function of coordination at all levels of decision-making, both in conditions of stable state regime and in variable market environments. The management system is a unique and dynamic task, and there is no specific recipe or recommendation of the best system. However, the main requirement in undertaking moderate changes in the system is the identification of those who will be affected by the changes and to what extent. In managing the system of urban mobility there are four interdependent factors of successful change processes:

- regulative and organizational regime of public transport services and other transportation services,
- charging and financial regime of public transport support,
- integration of mobility policy, urban planning and environmental protection,
- information technology system support of managing urban mobility.

In order to increase the usage and efficiency of urban public transport system it is necessary to study in more detail the factors that move or restrict the effects of this system. These are primarily social and economic criteria of efficiency – increased use of urban public transport system, improvement of the conditions of environmental quality or contribution to employment. In this group one has to mention the accessibility, quality, availability and affordability of public transport services. An important role lies also on the criteria of financial and economic efficiency, especially the internal cost efficiency and user-oriented offer. This complex assumes interconnected objectives and the functioning criteria of urban public transport. The current meeting of such objectives of the transport policy should be explained by a package of generic and locally specific historical factors. The policy success indication is the usage of the urban public transport system, which is composite indicator of numerous politically relevant criteria.

The characteristics of urban public transport system, articulated through the notions of share and quality, depend crucially on the package of critical conditions of success. The majority of these critical conditions are divided into four groups – external, strategic, tactical and operative. External conditions do not belong under the authority of urban public transport management, and therefore cannot be controlled – population, population density, population distribution, large incident gatherings and manifestations, etc. The objectives of urban public transport are under the influence of strategic factors, which are determined by various stakeholders, particularly national, regional and local authorities – political interests, specific regulation of urban public transport, integrated public transport and urban development. Tactical level refers to the issue of how general objectives can be reflected on the implementation of urban public transport services – organizational frames, financial frames, subsidies, public-private partnership and interfaces of urban public and other transport modes. The operative group of conditions contains the serving and performing of urban public transport services –

diverse offers (bus, metro, tramway, tricycle, cars, etc.), privileged position of urban public transport (the priority in using the infrastructure), traffic density (frequency, intensity), integration of public transport (maps, logistics, routes) and marketing and public transport information technology.

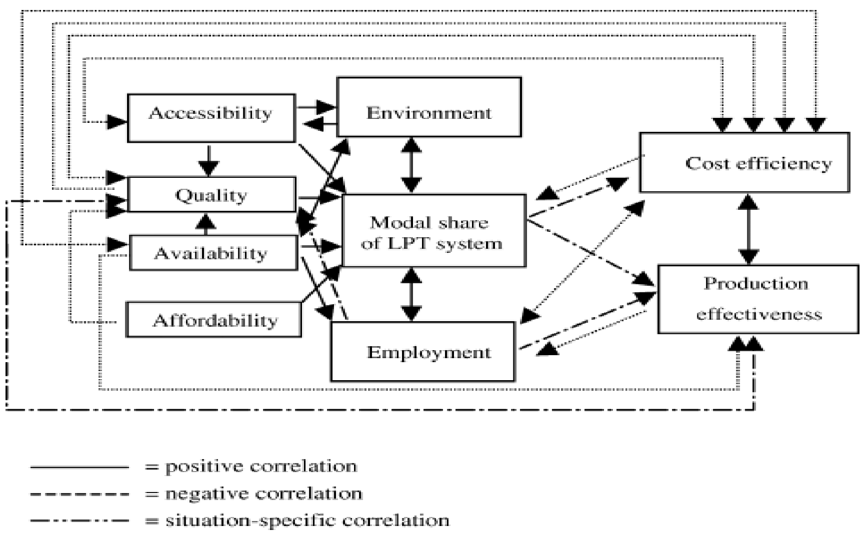

Fig.1. Interaction scheme of LPT objectives/criteria (adapted from Egmond et al,2012)

The recognition of interactions between modules and functions requires the development of compatible policies of both sides in the process of strategic transport planning. This is often combined in the transport plan and urban planning or the plan structures, which offers the strategic framework within which the modal and functional policy have been separately but consistently developed. Short-term plans often assume the form of rolling five-year program. The advanced management tools, such as planning, programming and budget system and the acceptance of a series of standards and guidelines for providing services can help in converting good planning into well guided implementation. An entire spectrum of strategic functions is usually developed for the agency at the level of metropolitan region, including: (World Bank, 2012)

- development strategy of urban planning;
- environmental protection strategy;
- road planning, including supervision of private concession development;
- transport management strategy;
- parking and road charging strategy.

Determining the scope of functions for metropolitan area management requires the development of integrated strategies, knowing that, due to the restrictions of the normal democratic process, this will start their implementation as well. The agencies have to act within these comprehensive strategic frames, regardless of whether they are part of the authority, quasi-authority or entity within the regulatory department.

In considering the applicable models and scenarios of the development of urban public transport in Croatia, the starting basis lies in evaluating the status of its establishing level, regulation level and organization level. About 70 per cent of population and about 80 per cent of traffic are concentrated in the urban areas of Croatia; the regulative of this transport segment at the government level does not exist, and the authority of managing urban transport has been delegated to the level of local authorities (Steiner et al, 2007). The municipal authorities have no autonomy of action in the transport regulation, there is a lack of integration of the segments of planning, monitoring, management and controlling of urban transport, and a large number of cities in Croatia have no organized urban public transport modes. While in bigger towns, such as Zagreb, Split or Rijeka, the solving of urban transport issues, due to negative impacts of uncontrolled growth in individual road transport on the quality of living has become a question of sustainability of further development, in smaller towns and urban settlements the failure to organize this transport mode has made the realization of the basic rights of citizens to mobility and freedom of movement questionable. The complexity of the problems regarding urban transport management is reflected in different, yet interdependent factors of influence:

- economic, regarding efficiency and effectiveness of the public transport system expressed in the value of transport effect and economic benefits,
- social, regarding provision of public services and the accessibility principles for all the citizens in all areas, and
- ecological, regarding provision of mobility which will not endanger the environmental protection and the health of people (Steiner et al,2007).

The areas of demographic policy, urban planning policy and environmental protection have to be integrated into the strategic planning and the policy of urban transport. Besides, the subsidiary objectives of sustainable development impose the implementation of the principles of integration, inter-modality and sustainability in the regulative and organization of urban transport. It is not possible to realize the required integration and implementation in the existing regulatory and organizational regime of urban transport in Croatia since in the existing system of "deregulated" urban transport management, the public authorities at the local level have neither the authority nor the autonomy, nor the competencies for such action (Steiner et al, 2007).

Therefore, the model assumes the regulatory organization of urban transport at all decision-making levels – state level and local levels of county and municipal authorities. The regulatory organization of urban transport, apart from the mentioned vertical coordination and cross-sector integration, assumes as well the horizontal coordination of the transport sector, particularly in the issues of modal structure of urban transport (modal share). At the state level and the local county level, it is necessary to organize the authorities for urban transport with the function of strategic planning of transport development and authority function in the standardization of minimal conditions of the construction, organization and regulation levels of urban transport, and other instruments in the realization of national and county strategic objectives, which principally or conditionally denote the segment of urban transport. In this context, these levels have to insure the budget means for the implementation of the dictated conditions in urban transport.

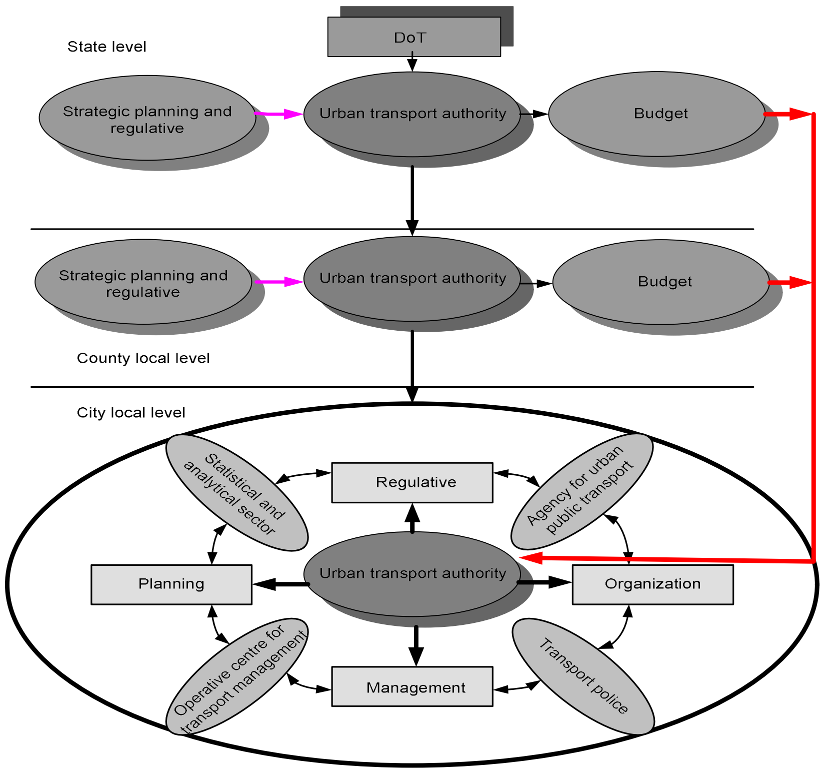

Fig.2: Optional Model of Urban Public Transport (Adopted Steiner et al, 2007).

According to the model, the Authority for urban transport at the local level of the city has the executive functions regarding strategic development and the policy of urban public transport – planning, regulative, organization and management of the urban public transport system. Therefore, urban transport authority at this level has to have the autonomy of action and budget means. Recognizing the good practice of separating the regulatory and operative functions, the model of urban public transport assumes the establishing of the Agency for urban public transport with the tasks of certification, licensing and concessions of operators in urban public transport and contracting of all the outsourcing arrangements for the realization of operational plans and programs in urban public transport. The organizational model of urban public transport should be based on the semi-market operational concept in order to insure a balance between the economic interests and the uniformity of the public service offer and quality of service. For the requirements of monitoring and management of urban transport as well as the public transport, the model foresees the establishment of a series of support units of urban transport entities – operational centre for transport management, statistical and analytical sector and urban transport police. The public transport segment, as part of urban transport, should not be treated here separately, and the model assumes that in these entities of planning, management and control, all the urban transport modes are uniformly represented and integrated.

2.3 Empirical Review of Intercity Travel Decision-Making

Trip purpose induces intercity travel. People make intercity travels only if they want to participate in some activities. The most common trip purposes are business, recreation, and personal activities. Business travel has a purpose usually associated with the travelers' work. The travel decision maker and cost payer are not necessarily the traveler. What is the primary concern in this kind of decision making may be the travel time, and/or on-time performance rather than travel cost.

These types of trips are not within the scope of this dissertation. All other trips are classified as non-business trips. The purposes for non-business trips could be recreation (i.e. vacation, sports or concerts, etc.), shopping trips, and personal activities, i.e. visiting friends, relatives or others.

Demand for non-business trips is different for different people. There is an enormous number of potential variables that have an impact on travel demand. The most frequently mentioned are household income, car ownership, and age (Tardiff, 1977, Damadaron, 1988, Koppelman, 1989). Income, a measure of the ability to afford travel, plays an important role in the determination of whether to travel due to the cost associated with intercity travel. Low income groups would not make many costly trips for social and recreational purposes, while higher income groups would be able to afford to do so. For many in the highest income groups, it would be expected to attend numerous social functions. Thus, household income would influence the number of intercity trips. It has been shown that car owning households make more daily trips, including car, bus, train, and air trips, than households without a car. However, in the intercity travel context, this is not necessarily true, especially in the way that the number of cars affects the number of trips.

Other socioeconomic factors, such as household size, age, gender, occupation, and education, also impact the possibility of making intercity trips. In contrast to urban trip length, which is within commuting distance, intercity travel is much longer. In 1995, the local mean trip length is 9.0 miles and the domestic long-distance mean trip length is 826 miles (US BTS 1999). This longer trip costs more and takes longer. Therefore, the cost and time spent on travel weigh more in the travel decision making process. Often the non-business trip is non-essential. It could be canceled or postponed for different reasons. There are various constraints when planning a non-business trip, such as destination limitations, available alternatives, and travel context and so on. If a trip purpose is to visit relatives or friends, usually the destination is the city where the friend/relative lives. In that case, destination is predetermined with trip purpose. However, for vacation trips, there exists a choice among different cities. More attractive cities are more likely to be chosen. Another constraint are the available mode alternatives and routes between the specific origin and destination. Within a corridor, for every available mode, the number of reasonable routes is limited. As a result, the route and mode constraints can be assumed underdetermined. When the destination to make the trip is decided, the available route and mode alternatives are already determined in the existing transportation system. Thus, only mode choice behavior is taken into account. The mode choice has to be based on the available alternatives. If the available alternatives change, travelers may adjust their trip plans within a period accordingly. Hence, the available alternatives exert an influence on the trip frequency. Among the available mode alternatives, the traveler chooses the one according to his/her preferences and constraints. For example, the income level of a household controls, to a large extent, the mode choice because it determines the amount of money available to be spent on travel. For the lower income groups, the relative costs of different alternatives of transportation would be of great importance in choosing a mode, while the higher income groups can afford to satisfy other preferences. Vehicle and licensed driver's availability also affect mode choice. If the household does not possess a vehicle and a licensed driver, then all travel must be undertaken using commercial carriers.

Attitude or personal preference also has an impact on the mode choice. For instance, if someone has a fear of flying, he or she may never choose an airplane as a transportation mode. The context of a trip is another factor influencing the mode choice. In the case of a big travel party, it is more likely to drive a car or van. The trip frequency affects the mode choice decision too. The available alternatives are characterized in terms of a set of modal attributes. There are many variables involved in describing the alternatives, such as travel time, travel cost, comfort, convenience, safety/security, reliability, etc.. Some of the variables are more directly causative than others for travel decision making. It is noteworthy that the safety/security became more predominant after the 9/11 tragedy (Liu and Li, 2003). However safety/security, comfort, reliability and convenience are not easy to measure, so it is difficult to incorporate them into the model. The most often used attributes are travel time and cost. Travel time is total elapsed time while traveling, which is usually counted from door to door because the travel status begins once travelers leave their starting locations and ends when the travelers reach their destination. Travel time can be segmented into line-haul time, access/egress time, waiting time, and transfer time. Travel time is one of the main factors impacting mode choice and trip generation. It is the attribute that travelers usually try to minimize or trade off when facing mode choice. Because the available time resource for traveling is limited, travel time also exerts an influence on trip frequency. The relative costs would have an effect on the choice of mode. For non-business trips, the absolute cost would affect the decision of whether or not to make the trip. For example, as the travel cost increases, the household plans its trips more carefully and makes fewer such trips as a result. The extent of the effect of cost depends on different travelers' attitudes, income, and other travel resources. From the above analysis, it is clear that the intercity decision-making process consists of several sub decisions, "when to travel", "where to travel" and "which mode to choose", all of which are interrelated. The different elements, such as socioeconomic factors, context of trips, and transportation system, have an impact on these sub decisions to different extents.

Often, trip generation refers to trip frequency. In this study, trip generation and trip frequency are used interchangeably. As defined in Section 2.1.2, they refer to the number of trips made during a given period of time. Thus, the study period length determines the possible trip quantity. Within urban travel analysis, often one day is set as a study period. The corresponding trip frequency can be very limited, such as 0, 1, 2.... The probability of a large trip frequency is very low. For instance, in the study of Domincich and McFadden (1996), only 4 out of 80 households surveyed made local shopping trips more than once. Daily intercity trip frequency, although not impossible, it is rare. An individual may take a certain number of trips in a period unless the time frame is so short that a majority of the travelers either do not make a trip or take only one trip. However, with cross-section data for just a short period, one has to consider that visits to a city may depend on recent trips to that city. Thus, a reasonable study period should be chosen to study intercity trip generation. In the 1995 American Travel Survey, the study period for intercity travel study is one year. The survey registered all journeys made by a sample of individuals during that period. Within the corridor context, the trip frequency can be as low as 0, or as high as 110. In the literature, the intercity trip frequency is considered to be either a discrete or continuous variable, and the rest of this section discusses these two choices. A discrete choice situation refers to one in which a decision-maker faces an option among a set of alternatives meeting the following criteria:

• The number of alternatives in the choice set is finite;

• The alternatives are mutually exclusive;

• The set of alternatives is exhaustive. Usually the choices that concern "how many" or "how much" of something (which is the choice of quantity) have alternative sets that are denoted by continuous variables. Standard regression procedures are appropriate for these continuous outcomes.

As Train (1986) argued, many a continuous variable can be represented, without loss of accuracy and sometimes with increased accuracy, by a discrete variable. Specifically when there is some conceivable maximum for the variable, the number of alternatives is finite and the choice situation could be discrete. In this case, choices of "how many" or "how much" are more fruitfully analyzed with discrete choice methods if the number of alternatives is fairly small. When there are a large number of alternatives such that the discrete dependent variable is essentially indistinguishable from a continuous one, standard econometric methods for continuous variables can be used adequately to represent the choice.

Typically, in an intercity travel demand analysis, the following decisions are accounted for: whether to travel, where to travel, and by what mode to travel. Commonly, two methods are used to carry out this travel behavior analysis: the separable/sequential analysis approach and the simultaneous analysis approach. Within the former, it is assumed that the decision-making process is sequential, in the sense that the decision of whether to travel does not affect the choice of the travel destination, and neither the time nor the destination influences the choice of the travel mode. These assumptions do not appear to be consistent with reality. Within the simultaneous approach, it is assumed that decisions of time, destination, and travel mode are made jointly. Accordingly, each sub decision interdepends on the others. Most of the time, the mathematical feasibility in practice is the main reason for the use of the sequential decision-making process. However, there still exists an unresolved question as to the order of the sub decisions. At least, no researchers have been able to justify the order they used.

It is more reasonable to incorporate the interrelatedness in the conceptual framework and model. The classical demand sub models are run independently, producing relatively disconnected estimates of trip generation, destination choice, and mode choice. Little attention has been given to the interdependent determinations of mode choice and trip frequency. Although the direct demand model combines all of the choices into one, it suffers from the lack of a behavioral basis. Ben-Akiva (1974) proposed a joint logit model in which both destination choice and mode choice are incorporated into one utility objective. However, this is not feasible for cases of high frequency. The model was extended by Adler and Ben-Akiva (1975) to trip generation, destination choice, and mode choice. However, the large amount of feasible combinations of frequency and modes make the calculation cumbersome. Thus, it still was not suitable for a large choice set resulting from all possible combinations of frequency, mode, and destination. The same problem occurs with the ordered logit model, or binary logit model for the frequency choice. Within the travel demand models of the literature (Sheffi, 1979; Vickerman and Barmby, 1985), the trip generation was considered as a binary choice problem of whether to make a trip. In the corridor context, individuals may make more than one trip within the one-year study period. So, there are a large number of binary nests if the binary logit model is used. Therefore, this type of discrete choice model for trip frequency will cause burdensome work. In these studies, trip generation was not interdependent with mode choice. The model proposed by Damodaran (1988) incorporated the mode choice into the ordered logit model. However, the interrelatedness between mode choice and trip generation happens only in the choice between zero trips and greater than zero trips. This does not appear to be consistent with reality. If the number of trips to be considered separately is even a small number, Damodaran's technique becomes very cumbersome. The model constructed by Domencich and McFadden (1996) is not completely interrelated because the utility functions are different for subdecisions even though the methodology utilizes an "inclusive price" variable that consists of the travel cost and time of the destinations. Subdecisions are estimated separately. Their model only considers the choice between no trip and one trip due to the limitations of the study case. The model structure only allows "one" or "no shopping" trips per household per day, which is an unrealistic set of choice for intercity travel on an annual basis.

In Koppelman's (1989) 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. In the model proposed by Kockelman and Krishnamurthy (2002), trip generation is considered continuous and derived from an indirect utility via Roy's Identity. The ratio between effective price and income, which is from the nested logit estimation for the travel subdecisions including mode choice and destination choice, is used for the trip generation model. The trip generation model and nested logit model for other subdecisions are estimated separately. The utility function for the logit model was not the same as the one used for trip generation. These reviewed models may be appropriate for the cases in their studies. However, when considering their transferability to the intercity corridor demand analysis, they are limited. The most common drawbacks are incapability of handling the high trip frequency, or inconsistency of the utility used in the trip generation and mode choice models, or the lack of interrelationships between trip generation and mode choice. So far, no models have solved all these problems within the intercity travel context.

2.4 Factors Affecting Travel Demand

2.4.1 The Price Effect

McFadden (1974) has revealed that price affects travel demand. In the case of the private car, demand increases when the user cost of the car falls. It also increases when income and the cost and waiting time for public transport increase. Likewise, demand for public transport travel rises when the user cost of the car increases and falls when the cost and waiting time for public transport increase.

Considering 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 (Goodwin, 1992). However, the value of the coefficients varies according to the model, the nature of the data (cross-sectional, time series, panel, short or long term) and the country (Hanly et al. 2002; Holmgren, 2007). Bresson et al. (2004) have also shown, in the case of public transport, that the elasticity of demand with respect to fuel prices is positive. However, this elasticity is lower than the fare variation elasticity of demand. This has led these scholars to judge that a fare reduction may play a substantial role in increasing public transport use. For Paulley et al. (2006), the fare elasticity of transport demand depends on the mode of transport and the period, 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.

2.4.2 The Income Effect

Travel demand is also affected by an income effect. Mogridge (1967) used the distribution of incomes and expenditures to estimate the number of cars there would be thirty years later. However, the values he obtained for the income elasticity and the price elasticity of car demand were criticized by Evans (1970) on the grounds that they did not take account of inflation. Dargay and Hanly (2002), and Bresson et al. (2004) have shown that it is a negative relationship between the number of bus trips and income level. Conversely, they have shown there is a positive relationship between income and car use. Economic growth leads, in particular, to higher car ownership rates (Ortuzar et al., 2006).

One of the difficulties of attempting to investigate income is that the effect of income is even more correlated with sociodemographic variables than the effect of the other variables (Garcia- Ferrer et al., 2006). These variables include household size (Lyons et al., 2002) and the economic situation (Gakenheimer, 1999).

The income variable also appears to reveal differences between countries. Dargay and Gately (1999) have shown, in connection with total vehicle stock and the economic development of different countries, that the rise in car ownership rates linked to rising per capita income, is greater the faster the country's economy is growing (as, for example, in South Korea and Taiwan). Button et al. (1993), paying particular attention to the lowest-income countries, have shown that car ownership rates become increasingly sensitive to income as these rates and income increase. However, while the stock of vehicles is dependent on per capita income levels, the level of market saturation varies according to the country with reference, in particular, to the user cost of the vehicle (Medlock and Soligo, 2002).

In order to consider the effect of income on travel practices, Schafer et al. (2000) bring in the concept of Travel Time Budget (TTB) developed by Zahavi (1973) and Roth and Zahavi (1981). Zahavi shows that "on average, humans spend a fixed amount of their daily time budget travelling", the travel time budget (TTB). Moreover, the per traveler travel time budget is typically higher for the lowest incomes (Roth and Zahavi, 1981). Over a wide range of income levels, Schafer and al. have made the assumption that the travel time budget was stable.

However, they made it clear that although the travel time budget remains constant on average, more detailed analysis may reveal a large number of variations. In the case of data for 1960-1990 for 11 regions, Schafer and al. have also shown that in those groups of countries with the highest incomes, such as North America and Europe, income and travel increase in the same proportions.

However, more detailed analysis reveals significant differences between these groups: for example, with a per capita income of $10,000, per capita travel in European countries attains only 60% of the level in North American countries. This difference reflects differences in infrastructure, urban density, population, and the user cost of transport modes. Similar cross-country differences in travel behavior have also been highlighted by van de Coevering and Schwanen (2006).

2.4.3 The Quantity Effect

Mogridge (1967; 1989) has shown that demand generally is also affected by quantity. This is assessed on the basis of available quantities of goods and services, measured in terms of the number of car trips, car ownership rates (Jansson, 1989) and the number of passenger-seat kilometers (Bresson et al., 2004).

More generally, an increase in the amount of a good that is available (cars or public transport) has a positive impact on demand. For the period between 1975 and 1995, Bresson et al. (2004) have shown that the reduction in public transport use was principally due to rising car ownership, although this effect has diminished over time with the slowing of the rate of increase in car stocks.

The quality of public transport, in terms of frequency, speed, network density and network access time has also been investigated (Vande Walle et al., 2006; Wardman, 2004; Paulley et al., 2006). The results nevertheless show that improvements in the quality of public transport ultimately result in a very limited increase in demand (Bresson et al., 2004).

2.4.4 The Spatial Effect

Lastly, travel demand is affected by spatial factors. Kain and Fauth (1977) have considered urban development as measured by the population density in each zone and the socioeconomic characteristics of the households and the location of their jobs and residences in order to explain their modal choice. Dargay and Hanly (2004) have highlighted the need to consider the relationship between transport and the use of space. For Small and Verhoef (2007), travel decisions are influenced by the density of buildings and the type of activity. Button et al. (1993) have demonstrated that there is a positive relationship between car ownership rates and the level of urbanization. But this relationship applies only up to a point. Beyond this point, the infrastructure becomes so saturated that the higher the urban density the more car use, car ownership rates, the number of trips and energy consumption are reduced (Camagni et al., 2002). This would lead to congestion and its attendant adverse effects.

Paulley et al. (2006) have shown that demand for bus transport depends on the residential zone. Individuals who live in rural zones with low population densities tend to be more dependent on car relying less on public transport, than those living in urban zones. The fare variation elasticity of bus travel in the English counties was calculated as –0.51 in the short term compared with –0.21 in metropolitan zones.

As Crane (2000) has reported, it remains difficult to identify how the use of urban space impacts on travel practices. Furthermore, Handy (1996) has shown that the urban activities mix has a negative effect on car use, while emphasizing the complexity of this finding. This complexity is also apparent when we consider the form of the city, even if a polycentric structure seems to result in lower energy consumption by traffic. This scholar shows, for example, that the larger the city the longer individuals' journeys, but the size of the city does not seem to have a direct effect on modal choice.

The user cost of a given transport mode, income and the available quantities of goods and services have therefore become classical structural variables for estimating intercity travel demand. Current practice is also to consider spatial variables when making estimates, but it seems easier to use urban density as a variable than urban form or the distribution of urban functions. However, variables that describe the quality of public transport services seem to have less of an effect on demand. Last, some questions about possible differences in travel practices between groups of countries remain unanswered.

2.5 Travel Demand Forecasting for Inter-city Urban Transportation

2.5.1 The Need for Determinig Travel Demand: Existing and Future

The basic purpose of transportation planning and management is to match transportation supply with travel demand, which represents 'need'. A thorough understanding of existing travel pattern is necessary for identifying and analyzing existing traffic related problems. Detailed data on current travel pattern and traffic volumes are needed also for developing travel forecasting/prediction models. The prediction of future travel demand is an essential task of the long-range transportation planning process for determining strategies for accommodating future needs. These strategies may include land use policies, pricing programs, and expansion of transportation supply – highways and transit service.

According to Chatterjee and Venigalla (2012), there are different levels of planning directed to different types of problems. The terminology for these levels of planning and analysis varies according to the context. For example, the expressions ‘micro’, ‘meso’, and ‘macro’ are sometimes used to describe the level of detail or the size of an area used for an analysis. Similarly, the expressions ‘site specific’, ‘corridor’, and ‘areawide’ or ‘metropolitan’ are used to describe variations in the scope of a problem. The approach and techniques for analyzing and forecasting travel would vary according to the level of analysis. Even for a particular level of analysis, the techniques may have to be adjusted to match the constraints of available data and manpower.

An example of a micro-level or site-specific analysis is the case of a congested road intersection. In this case traffic engineers would be interested in detailed traffic flow characteristics including turning movements of vehicles along each approach, and pedestrian volumes across each approach. Management strategies in this case would involve traffic operation and roadway design oriented techniques. A corridor level analysis on the other hand would cover a larger area, say, 16km and 3.2km wide. A major highway with severe congestion problem may require a corridor analysis. The origin and destination of trips, and modal choice of travelers would be of interest in this case. Station-to-station movements of passengers may have to be estimated in the case of a rapid transit service along the corridor. At the macro level the concern may be total energy consumption by the transportation sector or the total emission of an air pollutant; for these cases, information on total vehicle-miles traveled (VMT) on each functional class of roads will be needed.

It is important to recognize that the nature of problems to be examined dictates the level of planning to be used as well as the technique for travel demand analysis. The discussion of this study will be oriented mostly to 'meso' scale or areawide travel demand analysis that is commonly performed in urban transportation planning studies. Even for this type of analysis for an urban area at the 'meso' scale, the approach and details of techniques and models to be used would depend on the size of the area as well as the resources available for carrying out the work. For example, a small urban area may not have the manpower or funding needed for carrying out large-scale surveys and developing advanced mathematical models (Grecco, 1976).

2.5.2 Characteristics of Travel

There are certain special characteristics of travel demand that require recognition for planning and design purposes, and these are discussed below:

Spatial and Temporal Variations

The total magnitude of travel demand alone is not sufficient for detailed planning and management purposes. The spatial and temporal distributions of travel also are important items of information to be considered in determining supply strategies. The peaking of travel at certain time periods requires a level of transportation supply that is not needed at other times. However, due to the nature of supply which cannot be adjusted easily, large investments have to be made to provide roadway or transit service capacities to accommodate peak period travel, and this capacity is not utilized efficiently at other times. An imbalance in the directional distribution of travel also creates similar inefficiencies. The spatial orientation of trips has important influence on supply requirements and costs. A few typical spatial distribution patterns of trips in urban areas are listed below:

- Travel along dense corridors, which are usually radial connecting suburbs to central business district (CBD)
- Diffused travel pattern caused by urban sprawl
- Suburb to suburb or circumferential travel

• Travel within large activity centers in CBD and suburbs

Different modes of transportation may be needed to serve these different travel patterns. For example, fixed-route public transit service usually is efficient for concentrated travel along a dense corridor, but it is not ideally suited to serve a diffused travel pattern in a cost-effective manner.

Choice of domicile and work place, lifestyles and different travel needs of individuals and families make the comprehension of trip making characteristics of a large metro area very complex. Assume that this household has four members, including two kids who go to school, and two cars. It can be seen that there are at least 11 trips made by this household at different times of day. Most of the trips are auto trips and two trips are taken in the "walk" mode. Travel demand modeling attempts to capture such spatial and temporal variations in travel at an aggregate level, such as a zone, in which a number of households, businesses and offices exist (Grecco, 1976).

Classification of Travel by Trip Purpose and Market Segments

In addition to the spatial and temporal characteristics of travel demand, there are several other aspects of travel demand which must be recognized. 'Trip purposes' such as work, shopping, and social-recreation; and trip maker's characteristics such as income and car ownership, are important factors influencing the elasticity of demand reflecting its sensitivity with respect to travel time and cost. For example, ‘work’ trips may be more likely to use public transit for a given level of service than trips of other trip purposes. For a metropolitan study, it is useful to classify travel according to spatial orientation and trip purpose as shown in Figure 2. The concept of “market segmentation” is applicable to the classification of travel based on trip purpose, trip makers’ characteristics, and spatial-temporal concentration. This concept is used in the field of ‘marketing’ for developing different types of consumer products targeted to match different tastes and preferences of potential users/buyers of these products. The concept of market segmentation is applicable to public transportation planning. A single type of transit service is not suitable for all transit market segments. For example, express buses may be needed for a commuter market segment. Taxicabs serve a different market segment. Woodruff, et al (1981) examined this subject in depth.

2.5.3 Units for Measuring Travel Demand

Travel demand is measured and expressed in different ways for different types of analysis.

Examples of different units of measurement are:

a. Trip (between two areas)

b. Trip end (in a given area)

c. Traffic volume (on a road segment)

d. Person trip and vehicle trip

e. Passenger vehicle and freight vehicle

f. Person-km traveled and vehicle-km traveled

The definition of each of these units should be understood clearly, and an appropriate unit of measurement should be used to match the case being analyzed. For example, for a parking study, “trip end” is the appropriate unit for expressing parking demand. For estimating the number of lanes to be provided in a road segment, the demand should be expressed in terms of “traffic volume”. As it was pointed out earlier, the appropriate unit of travel for estimating fuel consumption and/or air pollution attributable to transportation is vehicle miles traveled (VMT).

Detailed information on existing travel is needed for two purposes: 1) Analyzing existing problems, and 2) developing mathematical models for forecasting travel. A variety of surveys can be performed for gathering information related to existing travel demand. However, travel surveys are expensive, and, therefore, care must be taken to identify the types of information that really would be useful for specific purposes, and then the most suitable procedures should be selected for gathering the information. Sampling techniques are useful, and adequate time and care must be devoted to developing sampling procedures. There are several different types of survey techniques, some of which are suitable for automobile travel, some for transit travel, and some for general passenger movement. Survey procedures for freight vehicles and commodity movements may be very different in certain respects from those of passenger travel. A few good references for inter travel demand related survey techniques Dresser and Pearson (1994), Stopher and Metcalf (1996), and Travel Survey Manual (1996).

2.6 Summary of Literature Review

Strengths and weaknesses of different models, including models in the literature and the proposed model, are discussed by model components: model type and aggregation level, model form, choice set, and data issues.

Since lower level activities may be aggregated into higher level activities, a model of lower aggregation level can be more flexible for practical applications and also can better explain travel behavior. For example, the impacts of raising fares on route and demand can be more accurately estimated by a city-pair demand model, rather than aggregate demand model, since a city-pair demand model can better capture a traveler' choice of connecting cities. Lower level aggregation models must take competition effects of alternatives into account. Although demand assignment models can be used to capture the competition effects, they implicitly assume total demand is inelastic. Demand generation models enable total demand to change with characteristics of alternatives. Thus, a model combines both demand generation and demand assignment is preferable.

In the literature, most travel studies only deal with either demand generation or demand assignment. Researchers may estimate these two types of models separately and apply these models sequentially-generating demands at one level of aggregation and then distributing the estimated volumes to lower-level components. For instance, Kanafani and Fan (1974) estimated demand generation and demand assignment models for city-pair-generated the city-pair demand first, and then distributed the total volume to different routes between these two cities.

CHAPTER THREE

RESEARCH METHODOLOGY

3.1 Research Design

The research design used was principally a survey method. Most of the transport companies surveyed do not maintain valid secondary data of their daily operations. If they do, they don't publish it. The transport routes operated, the conventional distance of the routes, the frequency of the trips for various routes, the estimated journey time, the fares charged at different route and the capacity of the various vehicles used were investigated .

3.2 Types and Sources of Data

The data used were secondary and unpublished data, consists of 19 directional O-D markets and the total number of travel products on the market filtered is 207 from 16 different transport companies with a terminal base at Owerri. The data collected include; the estimated travel times, frequency of trips at various routes, vehicles capacity, fare charged and travelled distance. Inter-city travel choices include multiple products which are unique combinations of cities from Owerri (see Table 3.1). The map in Figure 3 captures the pictorial view of the city-pairs explored in the study.

Figure 3: Map of Nigeria showing the Origin and Destination (OD) of Travel routes explored in the study. http://www.nigerianmuse.com

Several enumerators were employed at the terminals of the surveyed transport companies at different periods of the day all through the study period of two year. The data collected include the estimated travel times, frequency of trips at various routes, vehicle capacity, fare charged and travel distance.

Table 3.1: Travel Routes Surveyed

S/NO	ROUTE	DISTANCE IN KM
1	Owerri - Aba	69
2	Owerri - Abuja	733
3	Owerri - Awka	141
4	Owerri - Calabar	207
5	Owerri - Enugu	174
6	Owerri - Lagos	564
7	Owerri - Makurdi	397
8	Owerri - Okigwe	58
9	Owerri – Portharcourt	98
10	Owerri - Uyo	134
11	Owerri - Yenegoa	118
12	Owerri - Abuja	733
13	Owerri – Jos	757
14	Owerri - Kaduna	812
15	Owerri - Warri	207
16	Owerri - Abakaliki	213
17	Owerri - Benin	236
18	Owerri - Ibadan	508
19	Owerri - Sokoto	1299

Source: Inter-city online distance calculator software

Our specification captures these important service attributes of inter-city transport services.

In summary, 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 (see Table 3.2).

Table 3.2: Road Transport Companies Surveyed

S/No	TRANSPORT COMPANY
1	Associated Bus Company PLC (ABC)
2	Abia City
3	Abia Line
4	Akwa Ibom Transport Corporation (AITC)
5	Chisco
6	Constant link
7	God is Good
8	GUO
9	Heartland Express
10	Imo Express
11	Imo Transport Company (ITC)
12	Libra
13	Multi-Line
14	Peace Mass Transit (PMT)
15	Tracas
16	Youngs

3.3. The Demand Function

We determine the factors that explain the volume of passenger traffic generated by the bus terminals in Owerri municipality in the period 2013-2015. Demand for urban passenger movement may be influenced by several attributes as identified in literature. Indeed, the amount of passenger traffic that an urban area determined by closely related to frequency of vehicle trips, available bus fare, vehicular capacity, distance between origin and destination and journey time performance of vehicles of respective transport companies.

Hence, we estimated an equation that considers the determinants of inter-city urban passenger traffic in the sample of Nigerian bus terminal. Assuming that 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 the determinants of demand of inter-city urban passenger traffic in the sample of Owerri bus terminal within the period under study are as follows:

Following our analytical specification, we specify the following structured equation model for estimation in logarithmic form:

Model 1:

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

Model 2:

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

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 respective transport company

Dist = distance between origin and destination

Vcap = vehicular capacity

$\mathbf{D}_{totpax}$= demand expressed as total number of passengers

$\mathbf{D}_{pax\text{-}km}$ = demand expressed as passenger kilometer

We take the log of those independent variables for which logarithmic interpretations are meaningful. Second, log-linearity of the demand function implies that the underlying root function is of Cobb-Douglas (C-D) type. This may or may not be true. We make this assumption for two reasons: estimated coefficients of a demand function have interesting interpretations and can be easily compared with a vast number of other studies for which similar functions have been estimated; and, these functions are computationally less expensive. In a larger context, however, appropriateness of the functional form itself can be empirically tested.

3.4 The Estimation Method

By treating the regression function coefficients as elasticity coefficients, we estimated a log-linear relationship between travel demand (by public transport) and the explanatory variables of fare, frequency, vehicle capacity, distance and journey. This logarithmic transformation also has the benefit of reducing the risk of heteroskedasticity (Greene, 1993; Bourbonnais, 2004; Maddala, 2008) although it does not completely eliminate it. As stated by Maddala (2008), 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" (Maddala, 2008). Thus, heteroskedasticity means that the model is not convergent, which makes it less robust.

To estimate the model's unknown parameters, we first of all used the Ordinary Least Square (OLS) method and subjected the estimated variables to multinomial logit model. According to the proposed demand model, the following causal factors were utilized. There are fare, journey time, frequency, market distance, and vehicle capacity.

CHAPTER FOUR

DATA PRESENTATION AND ANALYSIS

4.1 Model Data

Inter-city transport market in this study 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

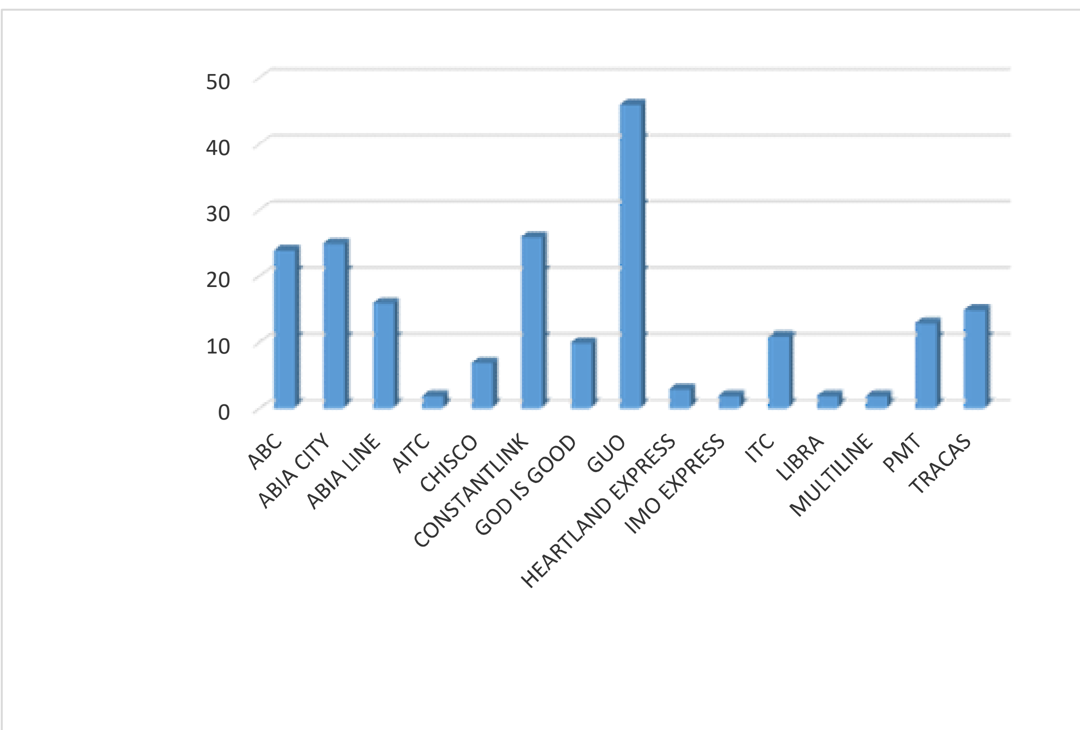

Fig.4: Bar Chart of Transport Companies Surveyed and frequency of Trips

Table 4.1: Summary of Urban Transport Companies Surveyed in the study

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: Author's Compilation (2016)

After the data were filtered based on the criterion of retaining routes with at least 2 daily trip frequency, 207 daily route observations to estimate the model.

The statistics for variables are computed using data of different time periods from 2014 to 2016. Market level variables, which are used to explain total demand of urban transport, are identical for all similar city-pair of a market. The statistics for these variables, therefore, are presented in terms of routes. The data used for estimating the model is filtered, in order to simplify the empirical work and ensure reliable data. This research uses Owerri based itineraries with non-zero fares.

4.2 Model Estimation

The basic strategy for estimating aggregate intercity travel demand models is to transform market share functions and then estimate parameters by linear regression. For the econometric models, the patronage of route is the basic determinant of demand. The natural logarithms of intercity travel market shares of two demand models are explored.

We attempt to identify factors that explain the volume of passenger traffic generated by the bus terminals in Owerri municipality in the period 2013-2015. Demand for urban passenger movement may be influenced by several attributes. Indeed, the amount of passenger traffic that an urban area can generate is closely related to frequency of vehicle trips, available bus fare, vehicular capacity, distance between origin and destination and journey time performance of vehicles of respective transport companies.

Hence, we estimate an equation that considers the determinants of urban passenger traffic in the sample of Nigerian bus terminal. Note that data for most of the explanatory variables is not available for, so this estimation refers only to the variables which are obtainable at bus terminals in Owerri (e.g. fuel cost data).

Assuming that potential travelers are homogeneous in the observed characteristics- no individual deviations (μ_{irt} = 0) except for the stochastic terms ε_{irt} 's, the equations to estimate the determinants of demand of urban passenger traffic in the sample of Owerri bus terminal within the period under study are as follows:

We specify the following models for estimation in logarithmic form:

Model 1:

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

Model 2:

$In^{D}_{pax-km} = \beta 1\ InFreq + \beta_2\ InFare + \beta_3 Jtim + \beta_4\ InVcap + \varepsilon irt$ …………..(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 respective transport company

Dist = distance between origin and destination

Vcap = vehicular capacity

$\mathbf{D}_{totpax}$= demand expressed as total number of passengers

$\mathbf{D}_{pax-km}$ = demand expressed as passenger kilometer

We take the logarithm of those independent variables for which logarithmic interpretations are meaningful. Second, log-linearity of the demand function implies that the underlying root function is of Cobb-Douglas (C-D) type. This may or may not be true. We make this assumption for two reasons: estimated coefficients of a demand function have interesting interpretations and can be easily compared with a vast number of other studies for which similar functions have been estimated; and, these functions are computationally less expensive. In a larger context, however, appropriateness of the functional form itself can be empirically tested.

This research chooses the aggregate demand forms for the market share (total number of passengers carried per day) function, and also estimates the aggregate demand model for another demand proxy (passenger-kilometer done per day) for comparisons. Routes are grouped in a city-pair by assuming that the routes with more common characteristics are more likely to be competitors, i.e. higher correlations among these routes.

4.3 Estimation Results

This research estimates proposed structural demand equations models in logarithmic forms consistent with econometric modelling. The detailed estimation results, therefore, are discussed by public transport companies (those selected within the study period) and then are combined in the summary in which the results of the OLS model with the same explanatory variables are also presented for comparison purpose. A multinomial logit model was estimated to determine if the travel behaviour was distant based – i.e. short distance or long distance.

Most coefficients of explanatory variables are statistically significant and have expected signs. Thus the null hypothesis **(H_{01})** is accepted, implying that service variables that impact on intercity travel demand are not correlated but distinct in attributes. All estimated frequency coefficients indicate that potential travelers prefer routes with high frequency, marginal effects of different frequency variables are different. The results confirm the alternate hypothesis (**H_{02}**) that the causal factors are critical to intercity travel service demand in Nigeria, and thus a proportional frequency increase on the segment with lower frequency increases service attractiveness more than an equivalent change on higher frequency segment.

After controlling for the other factors (such as fare, frequency, journey time and vehicle capacity) the coefficients of the route dummy variable still indicate that potential travelers strongly prefer direct routes, regardless of specifications and estimation methods. This validated the alternative hypothesis (**H_{03}**) implying that public transport companies in Nigeria adopt the direct routing structure.

Demand elasticities with respect to these variables and ratios of coefficients can be used to describe the structural changes over time. Whereas no specific time trends for scheduled flight time and fare effects are found, no structural changes related to other variables exist. Hence the null hypothesis (**H_{04}**) is accepted.

As shown in Table 4.1, most coefficients of explanatory variables are statistically significant and have expected signs. Thus the null hypothesis is accepted, implying that service variables that impact on inter-city travel demand are not correlated but distinct in attributes. Estimates from Model 1 and Model 2 method are listed in column (2) and (3).

Table 4.2: 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	*0.658*	*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: Author's Computation (2016)

The models above can be expressed in the following exponential form:

Model 1:

Demand (total no. of passenger) = $1.127 * Freq^{1.222} * Jtime^{-0.380} * Fare^{-0.236} * Dist^{0.083}$

Model 2:

Demand (passenger-km) = $1.590 * Freq^{1.266} * Jtime^{-0.206} * Fare^{-0.285} * Vcap^{00.165}$

The exponents are values of elasticity from Cobb-Douglas logarithmic derivation.

Although all estimated fare coefficients illustrate positive fare impacts on demand, the fare coefficients from Model 1 and 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 that potential travelers prefer routes with high trip frequency, marginal effects of different frequency variables are different. Differences in coefficient estimates among the different variables are less pronounced in the Model 1 results.

Although all coefficients of journey time indicate that travelers prefer routes with shorter journey time. The Model 2 estimates show that a one-minute increase of journey time on routes have a larger (about 1.206 times) impact of utility on direct routes.

4.4 Demand Elasticities

Demand elasticities with respect to different variables, among which fare is particularly of interest, are calculated and discussed first. The tables 4.1, 4.2 and 4.3 present the elasticity estimates (the beta-values of the structured equation model) of selected bus companies in Imo State.

Elasticity is a useful tool in demand analysis. As a result, many estimates of intercity travel demand elasticities, especially those with respect to fare, can be found in the literature on transportation. Comparing demand elasticities from our models to previous estimates helps us assess model validity. Elasticity, since it is dimensionless, also provides a convenient way to compare the relative importance of causal factors. This is particularly useful for log-linear models, since the estimated coefficients are elasticity values.

The estimated parameters of models (Table 4.4) are values of fare elasticities in the sample. In addition, the estimated elasticity with respect to fare is compared with their counterparts in the literature.

The demand elasticity with respect to a variable is determined by calculating the percentage change in demand resulting from one percent increase in the variable, holding all other independent variables fixed. This method is used to find route demand elasticities with respect to fare, frequency, vehicle capacity, route distance and journey time.

4.4.1 Demand Elasticity with respect to Fare

Fare elasticities of route demand are summarized in Table 4.4. Since potential travelers have more choices at route, fare elasticities of route demand are expected to be larger (in absolute values). While the fare elasticities calculated from OLS estimates, are consistent with the expectation. In addition, when market size (measured by the number of passengers) is taken into account, the elasticities generally become smaller in absolute values. Details of these elasticities are discussed by disaggregation level below.

Table 4.3: Fare Elasticity of inter-city travel demand

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

Source: Author's Computation (2016)

Fares are fundamental to the operation of public transport since they form a major source of income to operators. In general, if fares are increased, patronage will decrease. Whether revenue increases or decreases as a result of a fare increase depends on the functional relationship between fares and patronage as represented by the demand curve. Usually this is expressed through the concept of 'elasticity'. In its simplest form the value of the fares elasticity is the ratio of the proportional change in patronage to the proportional change in fares. It has a negative value when, as is usually the case, fares and patronage are inversely related: an increase in fares leads to a decrease in patronage and vice versa. If the value of the elasticity is in the range zero to -1, then a fares increase will lead to increased revenue. If the value exceeds -1, then a fare increase will lead to a decrease in revenue.

Fare elasticities are dynamic, varying over time for a considerable period following fare changes. Therefore it is increasingly common for analysts to distinguish between short distance and long distance-run elasticity values.

Fare elasticity varies significantly depending not only on the mode, and the time period over which it is being examined, but also on the specific circumstances in which a mode is operating. In the study, elasticity values from many sources were examined to provide an up-to-date overview of fares elasticities and the effects of various factors on the values. The principal results of this analysis are shown in Table 4.5. It can be seen that, broadly speaking, bus fare elasticity averages around -0.3 in the short distance and -0.4 in the long distance. There is evidence for this in Dargay and Hanly (1999) and Gilbert and Jalilian (1991).

Table 4.4: Comparison of Fare Elasticity of intercity travel demand with literature		
Scenario	**Fare Elasticity from this study**	**Elasticity from literature (Dargay and Hanly (1999) and Gilbert and Jalilian (1991).**
Short Distance	**-0.285**	**-0.30**
Long Distance	**-0.357**	**-0.40**

These results appear to indicate a significant change from those reported by Webster and Bly (1980), which were based on international aggregate measures of fares elasticity for all journey purposes and passenger types across all trip lengths and fares. 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 resulted in the then accepted 'standard' public transport fares elasticity value of -0.3.

The realisation that long-term elasticities can exceed -1 has serious implications for the public transport industry. While the immediate effect of a fare rise might be a temporary increase in revenue, the long-term effect is likely to be a decrease, although if future cash flows are discounted, operators may benefit from fare increases. Nevertheless, attempts to counter falling revenue with fare increases alone will eventually fail. Reversal of negative trends in public transport patronage requires service improvements, and possibly fare reductions.

The fare elasticities can be further investigated by their distributions and compared with other estimates in the literature. The fare elasticities from the OLS estimates indicate inelastic market demand. This indicates that fare elasticities of long distance traffic markets are higher than those of short distance traffic markets. A possible reason is that current fares in the long distance traffic markets are relatively high. Thus, a proportional fare increase reduces more service attractiveness in these markets.

4.4.2 Demand Elasticities with respect to Frequency

As suggested by Table 4.1, demand elasticities with respect to frequency variables are stable across routes- mainly due to their logarithmic functional form. The estimated frequency elasticities, however, vary slightly depending on model forms. This implies that positive distance elasticities are more likely to be found in higher traffic markets, which are usually better. All else being equal, while the influence of declining propensity to travel is more pronounced in better served markets, the influence of mode competition is stronger in minor markets.

Table 4.5: 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: Author's Computation (2016)

4.4.3 Demand Elasticity with respect to other Variables

The journey time and vehicle capacity elasticities are presented in Table 4.7. The vehicle capacity elasticity is smaller than journey time elasticities in absolute values (aggregate case). This indicates that the journey time elasticities of low traffic markets are higher.

Table 4.6: Other elasticities of inter-city travel demand

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

Source: Author's Computation (2016)

Applying the elasticity estimates and multipliers in Table 4.1 provides a guideline for the estimated demand elasticity by level of aggregation and by transport. It multiplies the estimate for the relevant level of aggregation by the relevant short-haul and long-distance elasticity multipliers.

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 though the prevalent public transport modes in Nigeria are the small capacity vehicles which offers a more flexible level of services

4.5 Estimated Travel Demand Based On the derived Intercity Travel Models

From the study, the following intercity travel models were deduced.

Model 1: **Demand** (total no. of passenger) = $1.127 * Freq^{1.222} * Jtime^{-0.380} * Fare^{-0.236} * Dist^{0.083}$

Model 2: Demand (passenger-km) = $1.590 * Freq^{1.266} * Jtime^{-0.206} * Fare^{-0.285} * Vcap^{0.165}$

We however attempt here to show the validity of the model by plugging values of the variables of the models. Table 4.7 shows the re sults of the estimation from routes chosen from four of the transport company operating from Owerri.

Table 4.7: Estimated Intercity Travel Demand of Selected Transport Companies in Owerri

Transport Company /Route	Daily Frequency	Journey Time	Fare	Travel Distance	Vehicle Capacity	Estimated Travel Demand from Model 1	Estimated Travel Demand from Model 2
Owerri - Awka (ITC)	3	2	1300	141	14	65	127
Owerri - Lagos (GIG)	4	8	6000	564	16	234	353
Owerri - Abuja (YSG)	5	9	7000	733	15	197	282
Owerri - Kaduna (ITC)	3	11	9000	812	30	98	147
Owerri - Calabar(AITC)	4	4	3500	207	13	78	133

Sources: Compiled by authors (2017)

It is shown that in a typical day, Imo Transport Company can have a daily passenger demand of 65 passengers to Awka or will have to satisfy 127 passenger kilometrage on a daily basis; and a daily passenger demand of 98 passengers to Kaduna or will have to satisfy 147 passenger kilometrage on a daily basis with their 30-seater buses in operation. Also, the God is Good motors can do have a daily passenger demand of 234 passengers going to Lagos or the equivalent of 353 passenger kilometres in a day. In addition, the Young Shall Grow Motors have available daily passenger demand of 197 passengers to Abuja route and a 282 passenger kilometer for that same route in a typical day. Finally, The Akwa Ibom Transport Company has an estimated 78 passengers and 133 passenger kilometers for Calabar route with 13-seater buses.

However, it is possible for any would-be operator determine the expected patronage on any route of operation using the derived models from this study. Thus this study has come up with empirical model to assess the viability of intercity passenger transport operation in Nigeria. However, it will also help the operators in business to do a sensitivity analysis based of changes in the intercity passenger travel markets in Nigeria. It can also help transport planners to determine the trip generation capabilities of various transport companies operating in a typical town.

The main objective of the proposed framework is to model aggregate route travel behavior and there should be revealed travel data to calibrate. The actual travel data is composed of trip frequency, travel distance, travel destination, travel activity, vehicle size, travel time, etc. Because all travel choices are based on existing transport supply, the available travel alternatives impact travel behavior. The level of service of the alternatives is described by travel cost, travel time, frequency, comfort, convenience, safety, reliability and so on. It is required to include the attributes of the available alternatives in the dataset. In summary, the data requirement for the proposed framework is at a transport company level. Future study should contain socio-economic characteristics of the travelers, revealed travel choice and related attributes, and the available travel alternatives.

4.6 Discussion of Findings

Combining the estimates by Model 1 and Model 2 methods,

Model 1: Demand(total no.of passenger)=1.127*Freq1.222*Jtime-0.380*Fare-0.236*Dist 0.083

Model2: Demand(passengers-km)=1.590*Freq1.266*Jtime-0.206*Fare-0.285*Vcap0.165

The Model **2** method,is the preferred model, since its estimates and implications are more sensible

The Model 2 outperform the other model. First, the Model 2 confirm the non-homogeneous correlations among alternatives, implying that the Model 2 incorrectly portray substitution patterns among route.

Table 4.8: 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: Author's Computation (2016)

Corrections for standard errors with more coefficients may be needed. Because the sequential estimation does not carry variances of inclusive values of more variables, the standard errors of more variable coefficients are usually underestimated, which may lead to invalid inferences and hypothesis tests. The standard errors presented in Table 4.1 are not corrected since most of the coefficients are very significantly different from zero. However, all the standard errors reported in this research are robust to heteroskedasticity and serial correlation, since error terms are unlikely to be independent and identically distributed.

Table 4.9: 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: Author's Computation (2016)

To distinguish between short-distance and long-distance inter-city travel demand behavior, we use longitudinal model. We use a multinomial logit specification to model the choice amongst these two different journeys. This specification allows us to test whether the factors associated with short-distance behavior are statistically different from the factors associated with long-distance behavior. If the factors affecting short-distance and long-distance behavior are similar, then a simple logit specification may be appropriate.

We model journey distance choice using a random utilities model in which individuals face two choices: short-distance(s) and long-distance (l). The utilities associated with each of these choices are designated Us and Ui respectively. This utility is modeled as a function of individual specific characteristics, X, that affect the utility associated with each choice differently. Hence,

$$U_{ji} = X_i\alpha_j + e_{ji} \quad \text{.....................(1)}$$

Where subscript j denotes the choice and subscript i denotes the individual. While we never observe utility, we can interfer from the choices people make how they rank some of these alternatives. Thus, if an individual chooses to persist, it must be the case that $U_s > U_l$ and $U_l > U_s$. If the e_{ji} are distributed Weibull, the differences in the ε are distributed logistic and a multinomial logit (henceforth MNL) can be used to estimate the differences in the parameters α (ie. $\alpha_s - \alpha_l$).

Table 4.10: Multinomial Logit Results for Aggregate Intercity travel Demand for short-distance and long-distance journeys

Variable	U_s	U_l
Frequency (trips per day)	**0.2744 [0.2622]**	**0.2744 [0.2622]**
Journey Time (minutes)	**-3.5050*** [0.5394]**	**3.5050*** [0.5394]**
Fare (in Naira)	**0.6709*** [0.2622]**	**-0.6709*** [0.2622]**
Vehicle Capacity	**-0.1911 [0.4323]**	**0.1911 [0.4323]**
Pseudo-R^2	*0.332*	*0.332*

Source: Author's Computation (2016)

P-values are used to judge the overall power of these explanatory variables to explain the outcome. The resulting test statistics allow us to reject the hypothesis that all variables are jointly one. The result for the test implies that there are significant differences between the factors associated with short-distance and the factors associated with long-distance inter-city travel behavior. This finding indicates that, contrary to the assumptions implicit in the literature, short-distance and long-distance inter-city travel behaviors are distinctly different choices.

CHAPTER FIVE

CONCLUSIONS AND RECOMMENDATIONS

5.1 Summary of Major Findings

Based on main empirical findings, including model forms, estimation methods and effects of causal factors are summarized as follows.

1. The pattern of correlations among alternatives is explicitly captured by applying log-linear model. The structure of the model implies that a route is more likely to compete with another route of the same O-D city- pair than the routes of the other O-D city pairs, and is least likely to be substituted by the non-road alternative.

2. The log-linear model employing passenger-kilometres is the preferred model for two reasons. First, the Model 2 models confirm 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.

3. 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 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 resulted in the then accepted ‘standard’ public transport fares elasticity value of -0.3 (Dargay and Hanly(1999) and Gilbert and Jalilian (1991).

4. All estimated frequency coefficients(1.266,1.247), indicate that potential travelers prefer routes with high flight frequency.
5. The vehicle capacity elasticity is smaller than journey time elasticities in absolute values (aggregate case). This indicates that the journey time elasticities of low traffic markets are higher.
6. There are significant differences between the factors associated with short-distance and the factors associated with long-distance intercity travel behavior. This finding indicates that, contrary to the assumptions implicit in the literature, short-distance and long-distance intercity travel behaviors are distinctly different choices.(See tables 4.8 and 4.9).

5.2 Conclusions

By reviewing the literature on intercity travel demand, this research finds that current understanding of the demand is lacking in several significant ways: (1) Most existing models only deal with either demand generation or demand assignment, or apply these two types of models sequentially; (2) How the relative importance of causal factors change over time is seldom studied; (3) The pattern of correlations among different alternatives is not well understood; and (4) Effects of market distance are under-investigated.

This research develops an O-D city-pair travel demand model and applies it to the land transportation system of Nigeria.

The model 2 improves existing models by adding preferred features and employing appropriate estimation method. The main model can handle activities at a low aggregation level (route level), and can be applied to a large network system and serves as a bottom-up policy analysis tool for different scenarios.

The model deals with demand generation and demand assignment in a single model. Thus, a change in a causal factor, such as a fare increase, may influence both total intercity travel demand and market shares of public transport companies in Nigeria.

5.3 Recommendations

The bottleneck of the planning of public transport systems is the knowledge of user demand. This knowledge is usually missing or only partly known. To solve this problem we built up a method to estimate the travel demand in time and space with high reliability. It means the estimation of an O-D matrix for public transport systems. The method was checked in practice. It proved that the method is good enough to use it in the normal day-to-day work for planning public transport systems.

Currently, the transport network models used to forecast travel demand do not have the capability to use these variables as inputs. It is critical, therefore, that we understand the way in which these variables are influencing mode choice, and are able to quantify them in a way that is compatible with the workings of the transport models. These improvements will ensure that the transport network models continue to be the optimum way of predicting future travel demand.

In order to increase the usage and efficiency of inter-city travel for public transport system it is necessary to study in more detail the factors that move or restrict the effects of this system. These are primarily, social and economic criteria of efficiency – increased use of the inter-urban transport system, improvement of the conditions of environmental quality or contribution to employment. In this, one has to mention the accessibility, quality, availability and affordability of public transport services.

An important role lies also on the criteria of financial and economic efficiency, especially the internal cost efficiency and user-oriented offer. This complex assumes interconnected objectives and the functioning criteria of inter-city public transport. The current meeting of such objectives of the transport policy should be explained by a package of generic and locally specific historical factors. The policy success indication is the usage of the inter- urban public transport system, which is composite indicator of numerous politically relevant criteria.

The characteristics of public transport system, articulated through the notions of share and quality, depend crucially on the package of critical conditions of success. The majority of these critical conditions are divided into four groups – external, strategic, tactical and operative. External conditions do not belong under the authority of urban public transport management, and therefore cannot be controlled – population, population density, population distribution, large incident gatherings and manifestations, etc.

The objectives of inter- urban public transport are under the influence of strategic factors, which are determined by various stakeholders, particularly national, regional and local authorities – political interests, specific regulative of urban public transport, integrated public transport and urban development. Tactical level refers to the issue of how general objectives can be reflected on the implementation of urban public transport services – organizational frames, financial frames, subsidies, public-private partnership and interfaces of urban public and other transport modes. The operative group of conditions contains the serving and performing of urban public transport services – diverse offers (bus, coaches, cars , etc.), privileged position of urban public transport (the priority in using the infrastructure), traffic density (frequency, intensity), integration of public transport (maps, logistics, routes) and marketing and public transport information technology.

5.4 Contributions to Knowledge

The model improves existing models by adding preferred features and using an appropriate estimation method. The model can handle activities at a low aggregation level (route level), and can be applied to a large network system. The model is applied to the domestic public transport network of Nigeria, and serves as a bottom-up policy analysis tool for different scenarios. The model deals with demand generation and demand assignment in a single model. Thus, a change in a causal factor, such as a frequency increase, may influence both total intercity travel demand and market shares of alternatives.

5.5 Suggestion for further Research

Nigeria as a developing nation needs model to analyze the significant changes she is undergoing, but as other developing nations she is with the least data infrastructure necessary to support these models. In this project we have developed methods for inter travel demand modeling that use available data and account for data limitations. We focus here on the data limitation that the public transportation network level of service measures are merely estimates with potential for large measurement errors. Measurement error is a serious issue, because it leads to inconsistent (i.e., wrong) estimates of the underlying parameters. As a solution, we propose to use the hybrid choice model framework, which incorporates travel time as a latent (i.e., unobservable) variable and uses measurement equations to link measured travel times with the underlying driving latent travel times. The latter is similar to the relationship in choice models where we use observed modal choices to provide information on the underlying latent utilities. With such a relationship, we can then potentially correct for measurement error and remove bias from the estimates.

While these initial results are promising, there are many directions for further research. One is to further develop the specification of the latent variable distribution (e.g., as a function of trip characteristics) as well as the measurement relationship between the measured travel time and the latent variable. It is also necessary to further understand the implications of these types of models on policy analysis.

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APPENDIX: OUTPUT

Descriptive Statististics from Transport Company Data

	N	Minimum	Maximum	Mean	Std. Deviation
Vehicle Capacity	208	7	58	14.79	9.829
Frequency	208	1	20	3.71	3.521
Journey Time	208	1	15	7.05	3.368
Distance	208	58	1299	460.57	253.395
Fare	208	500	6500	3502.79	1832.143
Valid N (listwise)	208				

MODEL 1:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.817[a]	.668	.658	.494

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.127	.406		2.780	.006
	FREQ	1.222	.064	.876	19.046	.000
	FARE	-.236	.063	-.247	-3.779	.000
	JTIME	.380	.137	.293	2.775	.006
	DIST	.083	.104	.076	.799	.425
	RDUMMY	.015	.008	.083	1.920	.056
	VDUMMY	.027	.038	.031	.712	.477

a. Dependent Variable: NOPASS

a. Predictors: (Constant), VDUMMY, FREQ, RDUMMY, FARE, DIST, JTIME

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	98.763	6	16.460	67.386	.000[a]
	Residual	49.098	201	.244		
	Total	147.861	207			

a. Predictors: (Constant), VDUMMY, FREQ, RDUMMY, FARE, DIST, JTIME

b. Dependent Variable: NOPASS

MODEL 2:

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.904[a]	.817	.811	.492

a. Predictors: (Constant), RDUMMY, VCAP, FREQ, DDUMMY, FARE, JTIME

ANOVA[b]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	216.873	6	36.145	149.381	.000[a]
	Residual	48.636	201	.242		
	Total	265.509	207			

a. Predictors: (Constant), RDUMMY, VCAP, FREQ, DDUMMY, FARE, JTIME

b. Dependent Variable: PASSKM

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.590	.476		3.342	.001
	FREQ	1.266	.065	.677	19.417	.000
	FARE	-.285	.065	-.222	-4.411	.000
	JTIME	1.206	.110	.693	10.951	.000
	VCAP	.165	.083	.069	1.988	.048
	DDUMMY	.711	.120	.296	5.925	.000
	RDUMMY	.000	.007	-.001	-.042	.966

a. Dependent Variable: PASSKM

MODEL FOR DISTANCE BASED

MODEL 2: DD: PASSKM

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
	DDUMMY = short distance (Selected)			
1	.832[a]	.691	.667	.513

a. Predictors: (Constant), RDUMMY, VCAP, JTIME, FREQ, FARE

Model Summary

ANOVA[b,c]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	37.122	5	7.424	28.233	.000[a]
	Residual	16.567	63	.263		
	Total	53.689	68			

a. Predictors: (Constant), RDUMMY, VCAP, JTIME, FREQ, FARE

b. Dependent Variable: PASSKM

c. Selecting only cases for which DDUMMY = short distance

Coefficients[a,b]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	1.851	.885		2.091	.041
	FREQ	1.281	.121	1.079	10.608	.000
	FARE	-.344	.083	-.425	-4.122	.000
	JTIME	1.302	.180	.804	7.214	.000
	VCAP	.356	.173	.172	2.053	.044
	RDUMMY	-.008	.011	-.056	-.719	.475

a. Dependent Variable: PASSKM

b. Selecting only cases for which DDUMMY = short distance

LONG DISTANCE

ANOVA[b,c]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	65.405	5	13.081	55.465	.000[a]
	Residual	31.367	133	.236		
	Total	96.771	138			

a. Predictors: (Constant), RDUMMY, VCAP, FREQ, JTIME, FARE

b. Dependent Variable: PASSKM

c. Selecting only cases for which DDUMMY = long distance

Coefficients[a,b]

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	3.493	1.447		2.414	.017
FREQ	1.247	.084	.775	14.796	.000
FARE	-.357	.260	-.122	-1.377	.171
JTIME	1.244	.220	.484	5.664	.000
VCAP	.111	.096	.059	1.154	.250
RDUMMY	.007	.011	.030	.579	.563

a. Dependent Variable: PASSKM

b. Selecting only cases for which DDUMMY = lo

MNL Model (Long Distance)

```
+---------------------------------------------+
| Multinomial Logit Model                     |
| Maximum Likelihood Estimates                |
| Model estimated: Apr 14, 2016 at 01:54:51PM.|
| Dependent variable               DDUMMY     |
| Weighting variable                 None     |
| Number of observations              208     |
| Iterations completed                  6     |
| Log likelihood function       -88.25131     |
| Restricted log likelihood     -132.1627     |
| Chi squared                    87.82277     |
| Degrees of freedom                    3     |
| Prob[ChiSqd > value] =         .0000000     |
| Hosmer-Lemeshow chi-squared =  98.78426     |
| P-value=  .00000 with deg.fr. =       8     |
+---------------------------------------------+
+---------+--------------+----------------+--------+---------+----------+
|Variable | Coefficient  | Standard Error |b/St.Er.|P[|Z|>z] | Mean of X|
+---------+--------------+----------------+--------+---------+----------+
          Characteristics in numerator of Prob[Y = 1]
 VEHCAP         .19110817      .43237482      .442   .6585    2.82211538
 FREQ           .27441101      .26223618     1.046   .2954    1.08653846
 JTIME         3.50503761      .53947223     6.497   .0000    1.73076923
 FARE          -.67096664      .19347820    -3.468   .0005    7.98076923
```

```
+----------------------------------------------------------------------+
| Information Statistics for Discrete Choice Model.                    |
|                            M=Model MC=Constants Only   M0=No Model |
| Criterion F (log L)      -88.25131      -132.16270    -144.17461 |
| LR Statistic vs. MC       87.82277          .00000        .00000 |
| Degrees of Freedom         3.00000          .00000        .00000 |
| Prob. Value for LR          .00000          .00000        .00000 |
| Entropy for probs.        88.25131       132.16270     144.17461 |
| Normalized Entropy          .61211          .91668       1.00000 |
| Entropy Ratio Stat.      111.84661        24.02384        .00000 |
| Bayes Info Criterion     192.51524       280.33800     304.36184 |
| BIC - BIC(no model)      111.84661        24.02384        .00000 |
| Pseudo R-squared            .33225          .00000        .00000 |
| Pct. Correct Prec.        87.98077          .00000      50.00000 |
| Means:       y=0    y=1    y=2    y=3    yu=4   y=5,    y=6   y>=7 |
| Outcome     .3317  .6683  .0000  .0000  .0000  .0000  .0000  .0000 |
| Pred.Pr     .3163  .6837  .0000  .0000  .0000  .0000  .0000  .0000 |
| Notes: Entropy computed as Sum(i)Sum(j)Pfit(i,j)*logPfit(i,j).      |
|        Normalized entropy is computed against M0.                   |
|        Entropy ratio statistic is computed against M0.              |
|        BIC = 2*criterion - log(N)*degrees of freedom.               |
|        If the model has only constants or if it has no constants,  |
|        the statistics reported here are not useable.                |
+----------------------------------------------------------------------+
```

MNL Model (Short Distance)

```
+---------------------------------------------+
| Multinomial Logit Model                     |
| Maximum Likelihood Estimates                |
| Model estimated: Apr 14, 2016 at 02:19:39PM.|
| Dependent variable              DDUMMY      |
| Weighting variable                None      |
| Number of observations             208      |
| Iterations completed                 6      |
| Log likelihood function      -88.25131      |
| Restricted log likelihood    -132.1627      |
| Chi squared                   87.82277      |
| Degrees of freedom                   3      |
| Prob[ChiSqd > value] =        .0000000      |
| Hosmer-Lemeshow chi-squared =  78.68865     |
| P-value=  .00000 with deg.fr. =      8      |
+---------------------------------------------+

+---------+--------------+----------------+--------+---------+----------+
|Variable | Coefficient  | Standard Error |b/St.Er.|P[|Z|>z] | Mean of X|
+---------+--------------+----------------+--------+---------+----------+
          Characteristics in numerator of Prob[Y = 1]
 VEHCAP       -.19110817      .43237482     -.442   .6585    2.82211538
 FREQ          .27441101      .26223618     1.046   .2954    1.08653846
 JTIME       -3.50503761      .53947223    -6.497   .0000    1.73076923
 FARE          .67096664      .19347820     3.468   .0005    7.98076923
--------------------------------------------------------------------+
| Information Statistics for Discrete Choice Model.                  |
|                            M=Model MC=Constants Only   M0=No Model |
| Criterion F (log L)      -88.25131       -132.16270    -144.17461 |
| LR Statistic vs. MC       87.82277           .00000        .00000 |
| Degrees of Freedom         3.00000           .00000        .00000 |
| Prob. Value for LR          .00000           .00000        .00000 |
| Entropy for probs.        88.25131        132.16270     144.17461 |
| Normalized Entropy          .61211           .91668       1.00000 |
| Entropy Ratio Stat.      111.84661         24.02384        .00000 |
| Bayes Info Criterion     192.51524        280.33800     304.36184 |
| BIC - BIC(no model)      111.84661         24.02384        .00000 |
| Pseudo R-squared            .33225           .00000        .00000 |
| Pct. Correct Prec.        87.98077           .00000      50.00000 |
| Means:       y=0    y=1    y=2    y=3    yu=4   y=5,    y=6   y>=7 |
| Outcome     .6683  .3317  .0000  .0000  .0000  .0000  .0000  .0000 |
| Pred.Pr     .6837  .3163  .0000  .0000  .0000  .0000  .0000  .0000 |
| Notes: Entropy computed as Sum(i)Sum(j)Pfit(i,j)*logPfit(i,j).     |
|        Normalized entropy is computed against M0.                  |
|        Entropy ratio statistic is computed against M0.             |
|        BIC = 2*criterion - log(N)*degrees of freedom.              |
|        If the model has only constants or if it has no constants,  |
|        the statistics reported here are not useable.               |
+--------------------------------------------------------------------+
```

TRP COY	FREQ	ROUTE	VEH CAP	J.TIME	DIST	FARE	PATRONAGE	PASSKM2	JTIME
ABIA CITY	8	Aba	7	1	69	600	56	3864	60
ABIA CITY	7	Aba	7	1	69	600	49	3381	60
ABIA LINE	9	Aba	7	1	69	600	63	4347	60
ABIA LINE	8	Aba	7	1	69	600	56	3864	60
TRACAS	10	Awka	7	1	141	1000	70	9870	60
TRACAS	10	Awka	7	1	141	1000	70	9870	60
TRACAS	2	Okigwe	7	1	58	600	14	812	60
TRACAS	2	Okigwe	7	1	58	600	14	812	60
PMT	10	Aba	15	1	69	500	150	10350	60
PMT	6	Okigwe	15	1	58	700	90	5220	60
ABIA CITY	7	Ph	7	2	98	1000	49	4802	120
ABIA CITY	7	Ph	7	2	98	1000	49	4802	120
ABIA LINE	7	Ph	7	2	98	1000	49	4802	120
ABIA LINE	7	Ph	7	2	98	1000	49	4802	120
TRACAS	5	Ph	7	2	98	1100	35	3430	120
TRACAS	5	Ph	7	2	98	1100	35	3430	120
ABC	3	Ph	14	2	98	800	42	4116	120
ABC	3	Ph	14	2	98	800	42	4116	120
IMO EXPRESS	3	Ph	14	2	98	800	42	4116	120
IMO EXPRESS	3	Ph	14	2	98	800	42	4116	120
PMT	12	Ph	15	2	98	800	180	17640	120
TRACAS	3	Enugu	7	3	174	1400	21	3654	180
TRACAS	3	Enugu	7	3	174	1400	21	3654	180
ABIA CITY	4	Enugu	7	3	174	1500	28	4872	180
ABIA CITY	4	Enugu	7	3	174	1500	28	4872	180
ABIA LINE	4	Enugu	7	3	174	1500	28	4872	180
ABIA LINE	4	Enugu	7	3	174	1500	28	4872	180
TRACAS	2	Yenegoa	7	3	118	1400	14	1652	180
TRACAS	2	Yenegoa	7	3	118	1400	14	1652	180
ABIA CITY	2	Yenegoa	7	3	118	1500	14	1652	180
ABIA CITY	2	Yenegoa	7	3	118	1500	14	1652	180
ABIA LINE	2	Yenegoa	7	3	118	1500	14	1652	180
ABIA LINE	2	Yenegoa	7	3	118	1500	14	1652	180
ABC	2	Awka	14	3	141	1050	28	3948	180
ABC	2	Awka	14	3	141	1050	28	3948	180
GUO	2	Awka	14	3	141	1050	28	3948	180
GUO	2	Awka	14	3	141	1050	28	3948	180
ABC	2	Uyo	14	3	134	1400	28	3752	180
ABC	2	Uyo	14	3	134	1400	28	3752	180
AITC	2	Uyo	14	3	134	1400	28	3752	180
AITC	2	Uyo	14	3	134	1400	28	3752	180

ABIA CITY	4	Abakaliki	15	3	213	3000	60	12780	180
ITC	4	Abakaliki	15	3	213	3000	60	12780	180
PMT	5	Enugu	15	3	174	1000	75	13050	180
ITC	2	Uyo	15	3	134	1600	30	4020	180
PMT	5	Yenegoa	15	3	118	1200	75	8850	180
TRACAS	2	Uyo	7	4	134	1800	14	1876	240
TRACAS	2	Uyo	7	4	134	1800	14	1876	240
ABIA CITY	6	Benin	15	4	236	3500	90	21240	240
CONSTANTLINK	2	Benin	15	4	236	3500	30	7080	240
God is good	2	Benin	15	4	236	3500	30	7080	240
GUO	2	Benin	15	4	236	3500	30	7080	240
ITC	6	Benin	15	4	236	3500	90	21240	240
TRACAS	2	Onitsha	15	4	86	1000	30	2580	240
ABIA CITY	2	Calabar	7	5	207	3500	14	2898	300
ABIA CITY	2	Calabar	7	5	207	3500	14	2898	300
ABIA LINE	2	Calabar	7	5	207	3500	14	2898	300
ABIA LINE	2	Calabar	7	5	207	3500	14	2898	300
TRACAS	2	Calabar	7	5	207	3500	14	2898	300
TRACAS	2	Calabar	7	5	207	3500	14	2898	300
ABIA CITY	2	Makurdi	7	5	397	4000	14	5558	300
ABIA CITY	2	Makurdi	7	5	397	4000	14	5558	300
ABIA LINE	2	Makurdi	7	5	397	4000	14	5558	300
ABIA LINE	2	Makurdi	7	5	397	4000	14	5558	300
ABC	2	Calabar	14	5	184	3000	28	5152	300
ABC	2	Calabar	14	5	184	3000	28	5152	300
GUO	2	Calabar	14	5	184	3000	28	5152	300
GUO	2	Calabar	14	5	184	3000	28	5152	300
ABC	3	Enugu	14	5	174	1500	42	7308	300
ABC	3	Enugu	14	5	174	1500	42	7308	300
GUO	3	Enugu	14	5	174	1500	42	7308	300
GUO	3	Enugu	14	5	174	1500	42	7308	300
ABC	2	Warri	14	5	207	3000	28	5796	300
ABC	2	Warri	14	5	207	3000	28	5796	300
MULTILINE	7	Warri	14	5	207	3000	98	20286	300
ABIA CITY	2	Calabar	15	5	207	3000	30	6210	300
ITC	2	Calabar	15	5	207	3000	30	6210	300
ITC	3	Makurdi	15	5	397	4000	45	17865	300
PMT	3	Makurdi	15	5	397	4000	45	17865	300
MULTILINE	4	Warri	30	5	207	2500	120	24840	300
ABIA CITY	6	Ibadan	15	7	508	4000	90	45720	420
ITC	6	Ibadan	15	7	508	4000	90	45720	420
PMT	2	Ibadan	15	7	508	4000	30	15240	420

ABIA CITY	2	Lagos	7	8	564	4000	14	7896	480
ABIA CITY	2	Lagos	7	8	564	4000	14	7896	480
ABIA LINE	2	Lagos	7	8	564	6000	14	7896	480
ABIA LINE	2	Lagos	7	8	564	6000	14	7896	480
ABC	3	Lagos	14	8	564	4000	42	23688	480
ABC	3	Lagos	14	8	564	4000	42	23688	480
ABC	2	Lagos	14	8	564	4000	28	15792	480
Chisco	5	Lagos	14	8	564	4000	70	39480	480
Chisco	5	Lagos	14	8	564	4000	70	39480	480
Chisco	5	Lagos	14	8	564	4000	70	39480	480
Chisco	5	Lagos	14	8	564	4000	70	39480	480
CONSTANTLINK	6	Lagos	14	8	564	4000	84	47376	480
CONSTANTLINK	7	Lagos	14	8	564	4000	98	55272	480
CONSTANTLINK	3	Lagos	14	8	564	4000	42	23688	480
CONSTANTLINK	2	Lagos	14	8	564	4000	28	15792	480
CONSTANTLINK	6	Lagos	14	8	564	4000	84	47376	480
CONSTANTLINK	7	Lagos	14	8	564	4000	98	55272	480
CONSTANTLINK	3	Lagos	14	8	564	4000	42	23688	480
CONSTANTLINK	2	Lagos	14	8	564	4000	28	15792	480
God is good	6	Lagos	14	8	564	4000	84	47376	480
God is good	6	Lagos	14	8	564	4000	84	47376	480
GUO	6	Lagos	14	8	564	4000	84	47376	480
GUO	7	Lagos	14	8	564	4000	98	55272	480
GUO	3	Lagos	14	8	564	4000	42	23688	480
GUO	2	Lagos	14	8	564	4000	28	15792	480
GUO	10	Lagos	14	8	564	4000	140	78960	480
GUO	5	Lagos	14	8	564	4000	70	39480	480
GUO	5	Lagos	14	8	564	4000	70	39480	480
GUO	6	Lagos	14	8	564	4000	84	47376	480
GUO	7	Lagos	14	8	564	4000	98	55272	480
GUO	3	Lagos	14	8	564	4000	42	23688	480
GUO	2	Lagos	14	8	564	4000	28	15792	480
GUO	10	Lagos	14	8	564	4000	140	78960	480
GUO	5	Lagos	14	8	564	4000	70	39480	480
GUO	5	Lagos	14	8	564	4000	70	39480	480
Libra	7	Lagos	14	8	564	4000	98	55272	480
Youngs	10	Lagos	14	8	564	4000	140	78960	480
ABIA CITY	9	Lagos	15	8	564	4000	135	76140	480
ABIA CITY	6	Lagos	15	8	564	4000	90	50760	480
CONSTANTLINK	2	Lagos	15	8	564	4000	30	16920	480
CONSTANTLINK	2	Lagos	15	8	564	4000	30	16920	480
CONSTANTLINK	2	Lagos	15	8	564	4000	30	16920	480

GUO	2	Lagos	15	8	564	4000	30	16920	480
GUO	2	Lagos	15	8	564	4000	30	16920	480
GUO	2	Lagos	15	8	564	4000	30	16920	480
Heartland Express	2	Lagos	15	8	564	4000	30	16920	480
Heartland Express	2	Lagos	15	8	564	4000	30	16920	480
Heartland Express	2	Lagos	15	8	564	4000	30	16920	480
ITC	9	Lagos	15	8	564	4000	135	76140	480
ITC	6	Lagos	15	8	564	4000	90	50760	480
PMT	2	Lagos	15	8	564	4000	30	16920	480
ABC	2	Lagos	58	8	564	6500	116	65424	480
ABIA CITY	2	Abuja	7	9	733	5000	14	10262	540
ABIA CITY	2	Abuja	7	9	733	5000	14	10262	540
ABIA LINE	2	Abuja	7	9	733	5000	14	10262	540
ABIA LINE	2	Abuja	7	9	733	5000	14	10262	540
CONSTANTLINK	5	Lagos	14	9	564	4000	70	39480	540
CONSTANTLINK	2	Lagos	14	9	564	4000	28	15792	540
CONSTANTLINK	5	Lagos	14	9	564	4000	70	39480	540
CONSTANTLINK	2	Lagos	14	9	564	4000	28	15792	540
God is good	5	Lagos	14	9	564	4000	70	39480	540
God is good	2	Lagos	14	9	564	4000	28	15792	540
God is good	5	Lagos	14	9	564	4000	70	39480	540
God is good	2	Lagos	14	9	564	4000	28	15792	540
GUO	5	Lagos	14	9	564	4000	70	39480	540
GUO	2	Lagos	14	9	564	4000	28	15792	540
GUO	5	Lagos	14	9	564	4000	70	39480	540
GUO	2	Lagos	14	9	564	4000	28	15792	540
ABIA CITY	8	Abuja	15	9	733	5000	120	87960	540
GUO	8	Abuja	15	9	733	5000	120	87960	540
ITC	8	Abuja	15	9	733	5000	120	87960	540
Libra	8	Abuja	15	9	733	5000	120	87960	540
PMT	3	Abuja	15	9	733	5000	45	32985	540
Chisco	2	Lagos	20	9	564	4000	40	22560	540
GUO	2	Lagos	20	9	564	4000	40	22560	540
GUO	2	Lagos	58	9	564	4000	116	65424	540
ABC	2	Lagos	58	9	564	6500	116	65424	540
ABC	3	Abuja	14	10	733	5000	42	30786	600
ABC	3	Abuja	14	10	733	5000	42	30786	600
CONSTANTLINK	4	Abuja	14	10	733	5000	56	41048	600
CONSTANTLINK	2	Abuja	14	10	733	5000	28	20524	600
CONSTANTLINK	4	Abuja	14	10	733	5000	56	41048	600

CONSTANTLINK	2	Abuja	14	10	733	5000	28	20524	600
God is good	4	Abuja	14	10	733	5000	56	41048	600
God is good	4	Abuja	14	10	733	5000	56	41048	600
GUO	4	Abuja	14	10	733	5000	56	41048	600
GUO	2	Abuja	14	10	733	5000	28	20524	600
GUO	4	Abuja	14	10	733	5000	56	41048	600
GUO	4	Abuja	14	10	733	5000	56	41048	600
GUO	2	Abuja	14	10	733	5000	28	20524	600
GUO	4	Abuja	14	10	733	5000	56	41048	600
Youngs	4	Abuja	14	10	733	5000	56	41048	600
CONSTANTLINK	2	Abuja	15	10	733	5000	30	21990	600
God is good	2	Abuja	15	10	733	5000	30	21990	600
GUO	2	Abuja	15	10	733	5000	30	21990	600
ABIA CITY	2	Jos	15	10	757	6000	30	22710	600
ITC	2	Jos	15	10	757	6000	30	22710	600
PMT	2	Jos	15	10	757	6000	30	22710	600
Chisco	2	Abuja	20	10	733	5000	40	29320	600
GUO	2	Abuja	20	10	733	5000	40	29320	600
GUO	2	Lagos	58	10	564	4000	116	65424	600
GUO	3	Lagos	58	10	564	4000	174	98136	600
Youngs	2	Lagos	58	10	564	4000	116	65424	600
Chisco	3	Lagos	58	10	564	6500	174	98136	600
ABC	2	Abuja	58	11	733	5000	116	85028	660
CONSTANTLINK	2	Abuja	58	11	733	5000	116	85028	660
GUO	2	Abuja	58	11	733	5000	116	85028	660
ABC	2	Kaduna	14	12	812	8000	28	22736	720
ABC	2	Kaduna	14	12	812	8000	28	22736	720
CONSTANTLINK	2	Kaduna	14	12	812	8000	28	22736	720
CONSTANTLINK	2	Kaduna	14	12	812	8000	28	22736	720
GUO	2	Kaduna	14	12	812	8000	28	22736	720
GUO	2	Kaduna	14	12	812	8000	28	22736	720
ABIA CITY	2	Kaduna	15	12	812	8000	30	24360	720
ITC	2	Kaduna	15	12	812	8000	30	24360	720
PMT	2	Kaduna	15	12	812	8000	30	24360	720
PMT	2	Kano	15	13	812	9000	30	24360	780
PMT	2	Sokoto	15	14	1299	10000	30	38970	840
ABC	2	Jos	14	15	757	6000	28	21196	900
ABC	2	Jos	14	15	757	6000	28	21196	900
CONSTANTLINK	2	Jos	14	15	757	6000	28	21196	900
CONSTANTLINK	2	Jos	14	15	757	6000	28	21196	900
GUO	2	Jos	14	15	757	6000	28	21196	900
GUO	2	Jos	14	15	757	6000	28	21196	900