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Analyzing the Microeconomic Determinants of Travel Frequency using the Com-Poisson Regression model

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***Abstract*—The paper provides insight on modelling the microeconomic determinants of individual travel behaviour using the Com-Poisson regression model. The level of trips towards a particular destination is used as a count variable. The model was applied to Mauritius, a small island state, where size is a constraint to travel demand. A survey was undertaken and the findings imply that age, sex, income, qualification, ownership of car and number of children are significant factors affecting travel behaviour. The Com-Poisson regression model is a promising technique to model travel behaviour which accounts for the non-negative integer value characteristic of travel frequency and future research on individual travel behaviour and mobility using this technique is proposed.**

Keywords-trips, travel behaviour, Com-Poisson

I. INTRODUCTION

Modelling travel demand behaviour has always been a challenge to analysts. Understanding the historic evolution of travel patterns and the response to changes in circumstances and economic factors is a necessary component in projecting future travel demand and assessing the influence of policy measures. Individual households' travel patterns change over the life cycle, are different for different generations and are influenced by spatial and socio-economic characteristics [1].

Transportation science has evolved considerably over time since the beginning of transportation as a field of scientific inquiry in terms of the theoretical and empirical determinants of travel behaviour, the measurement of travelling and the methods used to analyse data. Initially, the activity-based approach to model travelling demand had a profound implication on transportation research. The approach defines the motives for travelling to be linked to the activities which take place at the destinations and people confound utility for such activities and its relation to the activities which are conducted while travelling. According to this approach, travel has been taken as a derived demand, at least in an absolute term, but as Mokhtarian and Salomon [2] argue, a recent innovation has been to model travel demand as an end in itself - people enjoy undirected travel (a sense of speed, motion, control, enjoyment of beauty). This may motivate people to undertake excess travelling behaviour towards a particular destination. If the size of the country is a constraint to rising demand, then the frequency of travelling rises. This leads Anas [3] to conclude that formulating the travel problem in terms of trips undertaken help to treat the complementariness and substitution between consumption and travel.

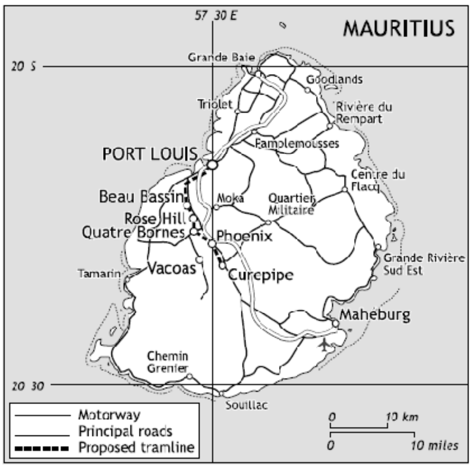
Measuring transport behaviour poses yet another challenge to analysts. Schafer [4] reviews such measurement and various indicators which have been used in the literature such as the travel time budget - defined as the time devoted to travelling - or the travel expenditure budget which is the money spent on travelling. However, over the years, indicators such as number of trips and the purpose of trips have been used to examine individual transport behaviour. One example is the operative traffic model for Copenhagen, called the Orestad traffic model (OTM), which consists of analysing the decision to participate in trips [5]. Ye et al. [6] also suggest that analysing the trips of individual provides a better understanding of travelling behaviour.

The frequency of trips has received little attention in empirical literature. This paper attempts to make three contributions: first, we model travelling behaviour through the number of trips which an individual has undertaken over a period of time towards a particular destination. The basic unit for measuring transportation activities is a trip, generally defined as a one-way move from an origin to a destination, motivated by a main purpose, and involving a public infrastructure [4]. Hence, as the number trips for one activity falls, trips for undirected travel demand may rise if travel demand is a seen a normal product.

Second, we model the number of trips as a count variable and apply the Com-Poisson regression as a novel approach to modelling travel behaviour within a socio-demographic framework. The model accounts for the integer value characteristic of the travel frequency variable. The distribution of the frequency variable is right skewed because it comprises a large proportion of zeros and this implies that conventional OLS estimation techniques are inappropriate [7]. In this context, count data models are a natural starting point for estimating the frequency of travel. The regression analyses the determinants of the frequency of travel taking into account the fact that it is a discrete variable that can only take nonnegative integer values. The model is proposed as a supplement to the OTM which is on based a binary logistic model. This novel approach may be compared to the limited dependent regression which is usually used to model transport behaviour, following the work of McFadden [8].

Thirdly, the study is conducted for a small island state like Mauritius. An understanding of the travel behaviour for Mauritius is even more challenging since over the last twenty years or so, the small, isolated, densely populated, developing Indian Ocean island of Mauritius has undergone and continues to undergo–a revolution in the way its society lives and works. Mauritius consists of a relatively small main island (58 km north to south by 47 km east to west), and various other scattered atolls. The main island has a high population density of 624 people per square kilometre and this is set to rise further by a steadily growing population. From a transport perspective, the case of Mauritius is interesting because it exhibits many of the transport problems facing other countries with land constraint, such as worsening congestion, air pollution and traffic accidents with limited size [9]. A major problem facing the island is the traffic congestion especially towards the city of Port-Louis and this has a negative impact on quality of life and on any economy and the society becomes stressful. Traffic congestion causes loss in productivity and time. The steady rise in internal road traffic has become a major problem with its impact also on land use, pollution and injury. Congestion is increasing the costs of doing business, as productive hours are wasted in traffic (and hence wasted fuel) and production schedules are disrupted. Congestion is ultimately resulting in a less productive economy and reduced quality of life.

The purpose of this paper is to obtain a better insight into the relative influence of socio-economic and demographic variables on travel behaviour by modelling the number of trips which individual undertakes towards the city of Port-Louis as shown in figure 1.



Source: Enocks (2003)

Figure 1. The Map of Mauritius

One factor further motivates our study. The transport sector is among the main sectors which represent the fastest growing source of Greenhouse Gases (GHGs) - a major source for global warming. A the same time, demand for travelling is expected to grow at a pace of economic growth which will eventually leads to rising GHGs. Either the distance travel increases with higher standard of living and/or the number of trips is expected to rise. In a small island such as Mauritius, the size of island limits the increase in distance travel and hence, people have a tendency to compensate the demand for travelling through higher trips towards a particular destination. Understanding the behavioural dynamics of travel frequency is therefore an important contribution towards land transportation planning.

The paper is organized as follows: In section II, a brief review of literature on modelling travel behaviour is provided; Section III deals with the methodology and data modelling; Findings and discussions are presented in section IV; and Section V concludes.

II. MODELLING TRAVEL BEHAVIOUR - A BRIEF REVIEW OF LITERATURE

Modelling travel demand, within transportation science, has a rich literature on both the theoretical dimension as well as on the empirical dimension. The theoretical dimension was formulated as a response to a major criticism of the neo-classical theory of consumer behaviour which ignores the spatial nature of consumption and fails to account for a fact that most consumption cannot be realized without incurring travel or communication costs [3]. Becker's theory of allocation of time assumes that travel is intimately related to both consumption and the allocation of time among discretionary activities, but overlooked explicit treatment of travel itself as an activity [10]. Location theory and urban economics did not help to provide a formulation of the demand for travel. For instance, the conventional location theory, assumes that the consumer travels to the nearest store or destination while in urban economics, it is standard to assume that the consumer commutes a rather non-standard manner such that the consumer will not travel in any other way.

The empirical dimension of travel demand has developed independently of standard microeconomic theory, mainly due to the contribution of McFadden's econometric formulation of the problem [8]. Most of travel demand analysis has, thus, its roots in applied econometric techniques and especially in discrete choice models.

An important component in empirical analysis is the measurement of travel behaviour. Gordon and Richardson [11], for instance, use the number of trips as an indicator for travelling and conclude that for the period 1969 to 1995, the average commuting time in the US fell but the total vehicle miles have increased during the same period. Some of the higher vehicle miles may have come about because people travelled longer distances at higher speeds on their commutes, but most of it is likely to have come from a larger number of discretionary trips. Anas [3] further adds that the travel demand problem can be and should be defined more generally by how many trips and what kind of trips to make over a period of time and to which destinations. Theoretical foundation of trips as indicator of travel behaviour may be found in Bacon [12] which constructs a utility-maximizing model of the optimum frequency of shopping at a given centre.

The number of trips is a major component of transport research especially for policy making. The operative traffic model for Copenhagen, called the Orestad traffic model (OTM), is a state-of-practice for modelling passenger travel demand. The OTM is a trip-based or tour-based modelling approach where a tour is defined in the OTM to be a sequence of only two trips, i.e. a trip from home to the destination and a return trip from the destination to home, without intermediate stops. Schafer's cross country analysis provides ample evidence of changing behaviour associated with trips [4]. The survey shows that at low mobility levels, one trip in a day is dedicated to a combination of work (short term survival) and education (longer term well-being), and about half a trip on average is dedicated largely to personal business (essentially, shopping at local markets). Over time, decentralisation of work in many countries leads to lower trips being undertaken for work related purpose but trips for non-work discretionary purposes rise. The reasons for the proliferation of non-work discretionary trips are easy to conjecture. First of all, jobs and residences have decentralized, reducing the average distance between homes and employment concentrations to which non-work trips are made. Incomes have increased and as incomes increase the demand for product variety grows and consumers seek a larger diversity of opportunities to shop, purchase services and engage in recreation or leisure-related activities. As incomes increase, car ownership also increases and the availability of multiple private vehicles or of more persons with access to a private vehicle stimulates more travel and discretionary mobility [3]. To close the gap between the theoretical dimension and empirical dimension of demand travel, formulating of the travel problem in terms if trips undertaken help to treat the complementariness and substitution between consumption and travel. While recognising that travel is necessary for consumption, it also competes with consumption for income and time, that there are many alternative "shopping" destinations available to modern consumers, that such destinations are substitutes and that the degree of substitutability varies. Over the past years, there has been considerable research on people's trip patterns. Recent development includes the analysis of trip chaining patterns [5].

III. Methodology and Data Modelling

The determinants of travel behaviour may be classified into three dimensions: (i) the spatial dimension, (ii) the socio-economic dimension, and (iii) the personality dimension. The spatial dimension is an important part in the activity system approach in which daily activity and travel can be analyzed. Living, working, shopping, and recreation are spatially separated activities, inducing the need to travel. Consequently, travel demand does not derive its utility from the trip itself, but rather from the need to reach locations where activities take place. For that reason, the configuration of activities, i.e., the land use pattern, characterized by density, diversity, and design among others is likely to influence travel behaviour. The spatial component is our analysis is accounted for by modelling the number of trips towards one reference destination which is the city of Mauritius, Port-Louis.

The focus of the study is on individuals and their characteristics. Age, gender, household size, income, level of education, employment status, and mobility constraints are commonly used variables [1]. Evidence on the effect of age on travel behaviour suggests that car ownership is lower among young and older people. Thus, older people walk more often and public transport usage is greater. Moreover, if older persons travel by car, they travel shorter distances. However, travel itself may have socializing opportunities for older people. Thus, non-work trips have, therefore, been found to be highest among older people. Therefore, the impact of age is ambiguous and demands empirical evidence.

As in many developing countries, car use is generally found to be lower among Mauritian women than men. Women travel more often by public transport, or on foot. As women are more reliant on slow modes, they cannot travel such long distances as their male counterparts. This difference may be explained by, among others, their lower wages and the fact that women obtain different types of jobs to man. The cultural aspect also plays an important role in determining travel behaviour of women. Travel tends to be less in conservative religious setting. However, because women remain responsible for most household maintenance tasks, non-work trips may be higher.

Household size is positively associated with car ownership. Because of intra-household decisions related to the activities of several household members, it may be appropriate to own more cars. Consequently, car use is higher, and use of public transport and walking are lower within large households As these households are more car dependent, they wish to travel longer distances. But if size is a constraint, then, the number of trips will increase. We test the effect of household size through the number of children in the household. A positive relationship is expected.

Educational level, employment status, and income may be interwoven. Highly educated workers are more involved in jobs with a higher occupational status, which results in higher incomes. Consequently, studies of the effects of educational level, employment status or income on travel behaviour can result in comparable findings. For example, higher car use, longer travel distances and travel times can be found across highly educated people, employed people, and high income groups These people often obtain jobs with a high occupation status that are concentrated in high-density office parks. As a result, highly-educated people and high-income groups are more involved in higher number trips. Our empirical analysis takes into account only education level to avoid any simultaneity bias.

Car ownership can be analyzed as an endogenous variable which is explained by various socio-economic variables. Highly educated people are found to own more cars. Due to relationships between education and income, car ownership is higher across high-income groups as well. On the other hand, car ownership can be considered as an exogenous variable, explaining travel behaviour. Ownership of car may be lead to higher number of trips.

Based on the above theoretical explanatory variables, a survey of 1000 respondents was undertaken where respondents in the person sample were asked to report the number of trips undertaken during the particular reference week. The destination was the city of Port-Louis and the origin involves various points around the island. Mauritius is divided into nine districts and the sample has been stratified according to the population of the districts, excluding Port-Louis. The points were chosen at random using the random street approach and involves equal number of male and female.

TABLE I. VARIABLES DESCRIPTIONS

Variables	Characteristics
Age	Continuous
Sex	Binary: Male =1; Female =0
Income	Binary: High=1; Low=0
Model of Transport	Binary: Car = 1; Bus=0
Number of children less than 18	Continuous
Qualification	Primary =1; secondary = 2; and tertiary =3

From the data collected, we note that the mean of the response variable is greater than the variance. This indicates under-dispersion. In statistical literature, under-dispersion is handled through various generalized forms of the Poisson distribution such as the Generalized Poisson distribution [13,14] and the class of weighted Poisson distributions [15]. However, modelling of under-dispersion by the Generalized Poisson distribution may not always be efficient [14]. In this paper, we emphasize on one of the weighted Poisson distributions that have become increasingly popular in the recent years known as the Conway Maxwell Poisson or Com-Poisson distribution (CMP) [16]. This distribution has elegant statistical properties such as its flexibility to model both over-,equi- and under-dispersed data. Moreover, it forms part of the family of exponential dispersion models and is a generalization of some popular discrete distributions such as the Geometric, Poisson and Negative-Binomial distributions. In fact, Shmueli et al.[16] have shown that CMP yields fits with almost equal efficiency as the negative-binomial model and other discrete distributions. Besides, its generalized linear model (GLM) has also been established. In the regression set-up, Jowaheer and Mamode Khan [17] has developed the Com-Poisson (GLM) and studied its application to set up a regression model for analyzing car breakdowns in Mauritius [18]. In this paper, we use their Com-Poisson GLM to set up a regression model between the number of trips an individual undertakes to Port-Louis in relation with his age, sex, level of income, his mode of transport, the number of children he has and his qualification level. More specifically, the covariate sex will be coded as 1 for Male and 0 for female. His level of income will be classified into two categories: high income (> Rs 15,000) coded as 1 and low income (< Rs 15,000) coded as 0. Since the most common mode of transport in Mauritius is car, we categorize this variable as : car-usage coded as 1 and non-car usage as 0. As for the number of children, we focus on school children less than 18 years old. Finally, the level of qualification is split into three types: primary coded as 1, secondary coded as 2 and tertiary coded as 3. To estimate these regression parameters, we will refer to the joint quasi-likelihood estimation approach (JQL) developed by Jowaheer and Mamode Khan [17] and Mamode Khan and Jowaheer [18]. In the next section, we present the Com-Poisson regression model and the JQL approach.

A. Com-Poisson Regression model (CPRM) and the quasi-likelihood estimation technique

Let y_i be the number of trips for the i^{th} individual $(y_i > 0, i = 1,2,3,...,1000)$ and x_i be the 7-dimensional vector of covariates corresponding to y_i. Let β be the 7-dimensional vector of covariates such that β_j $(j = 1,2,3,...,7)$ is the regression effect of the j^{th} covariate on the number of trips. The Com-Poisson regression model is given by

$$P(Y = y_i) = \frac{\lambda_i^{y_i}}{(y_i!)^{\upsilon}} \frac{1}{Z(\lambda_i, \upsilon)} \tag{1}$$

where

$$Z(\lambda_i, \upsilon) = \sum_{j=0}^{\infty} \frac{\lambda_i^j}{(j!)^{\upsilon}}, \lambda_i > 0, \upsilon > 0 \tag{2}$$

and

$$\ln(\lambda_i) = x_i^T \beta \tag{3}$$

Note that $\lambda < 1$ indicates over-dispersion, $\lambda = 1$ indicates equi-dispersion and $\lambda > 1$ indicates under-dispersion. Following Shmueli et al. [16] , equation (2) can also be approximated by

$$Z(\lambda_i, \upsilon) = \frac{\exp(\upsilon \lambda_i^{\frac{1}{\upsilon}})}{\lambda_i^{\frac{\upsilon-1}{2\upsilon}} (2\pi)^{\frac{\upsilon-1}{2}} \sqrt{\upsilon}} \tag{4}$$

To estimate the parameters β and υ, we solve the joint quasi-likelihood equation

$$\sum_{i=1}^{1000} D_i^T V_i^{-1} (f_i - \mu_i) = 0 \tag{5}$$

where $f_i = (y_i, y_i^2)$ and $\mu_i = (\theta_i, m_i)$. Note $\theta_i = E(Y_i) = \frac{\lambda_i^{\frac{1}{\upsilon}}}{\upsilon} - \frac{\upsilon - 1}{2\upsilon}$ and $m_i = \theta_i^2 + Var(Y_i)$, where $Var(Y_i) = \frac{\lambda_i^{\frac{1}{\upsilon}}}{\upsilon}$. The components of D_i and V_i are derived following the approach of Jowaheer and Mamode Khan [17]. The JQL equation (5) is solved iteratively using the Newton-Raphson technique, i.e,

$$\begin{pmatrix} \beta_{r+1} \\ \upsilon_{r+1} \end{pmatrix} = \begin{pmatrix} \beta_r \\ \upsilon_r \end{pmatrix} + \left[\sum_{i=1}^{1000} D_i^T V_i^{-1} D_i \right]^{-1} \left[\sum_{i=1}^{1000} D_i^T V_i^{-1} (f_i - \mu_i) \right] \quad (6)$$

IV. FINDINGS AND DISCUSSION

In this section, we apply the JQL equation (6) to obtain estimates of the regression parameters. The following table shows the regression estimates for the various covariates. The covariate of age is negative and significant. This implies that older people have a tendency to undertake less trips towards Port-Louis. One major reason may be because of the spatial characteristics of the place in terms of its high temperature and population density, among others. The finding also implies that the frequency of travelling towards our reference destination is higher for younger people.

TABLE 2.

	Estimates	Standard Error
Intercept	2.341	(0.131)
Age	-1.219	(0.234)
Sex	3.552	(0.188)
Income	4.557	(0.372)
Mode of transport	7.211	(0.213)
Number of children	-2.011	(0.115)
Qualification Level	6.710	(0.381)

The positive covariate associated with sex implies that gender plays a role in travel behaviour. As stated previously, family setting, women status and their occupation as well as the low ownership of car may explain the conclusion that women undertake less trips than men.

As expected, high income, high qualification and ownership of car enhance the demand for travelling. Both covariates are positive and significant. This may have major implication for transport policy. Due to the recent economic progress in Mauritius, the population have a craze for purchasing car and our analysis suggests that the number of trips is likely to increase to Port-Louis and the problem of congestion will further rise.

The covariate with household size proxied by the number of children is negative. This differs from our theoretical expectation that higher household size leads to higher trips. A possible explanation is that household with children may choose other destinations for travelling purposes.

V. CONCLUSION

The study provides an analysis of travel behaviour using major determinants at individual level using a novel regression technique – the Com-Poisson model. The analysis considers the number of trips, which is undertaken towards particular destination, as a count variable. The use of a reference destination provides a close examination of the socio-economic determinants for the motive to travel to that particular destination. Such analysis may be use for projecting future mobility in our reference area. The Com-Poisson regression uses the number of trips as account variable and such model may be distinguish between binary model which analyses the determinants of the decision whether or not to travel. Planning policies based on the activity approach attempt to reduce travel by increasing cost or by bringing destinations closer to origins. However, our study shows that the frequency of travelling may rise and such conclusion should be accounted in transport policies. Using the number of trips as a count variable and the Com-Poisson regression technique, the analysis may be extended to account for more socio-economic characteristics such as family types, purpose of travelling and personal preferences of individuals. Compared to binary models, which correspond to the decision to participate in the activity, analysing the frequency of trips using Com-Poisson accounts for the skewness of the data. A major limitation of the current study is the limited number of explanatory variables which are used in the regression model. This provides opportunities for further research.

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