AN ANALYSIS OF THE EFFECT OF LOCATIONAL FACTORS AND ACCESSIBILITY ON DISCRETIONARY TRIP GENERATION USING AN ORDERED RESPONSE MODEL

by

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spatial transfer of an ordered response model. Investigating the impact of a scaling updating technique on the transferred ordered response model in another spatial context is the second objective. The results of this spatial transferability analysis show that a directly transferred model (without any updating of the transferred coefficients) performs reasonably well in predicting the choice probabilities in the application (new) context. Revising the constant terms and scalars in the ordered response model using the scaling updating technique substantially improves the predictive ability of the transferred model.

Overall, two implications can be identified from these analyses. First, the ordered response model is a useful methodology for the analysis of trip generation. The trip-making decision should therefore be treated as a multiple response with a natural order, not as a continuous variable or a dichotomous response. The other implication is that while weekday, home-based shopping trip generation is sensitive to the location of the households, the gravity-based measure of accessibility was not found to be a significant factor in the trip-making decision.

ABSTRACT

The research reported in this thesis constitutes an attempt to address some of the methodological problems in the existing Urban Transportation Modelling System for trip generation analysis, and to provide new empirical evidence on the effect of locational factors and accessibility on discretionary trip making using data from the Greater Toronto Area (GTA).

Three separate analyses were performed using an ordered response model, a type of discrete choice model that exploits the ordering of information in the dependent variable in situations where there are more than two responses. One type of analysis examined the effects of geographic location of households on weekday, home-based shopping trips. Five zones (planning districts) within the GTA were chosen to reflect different types of location. The statistical results of this analysis show that, after controlling for some household's socio-economic characteristics, its location within the metropolitan area has some effect on its weekday, home-based shopping trip generation. In particular, households located in the older urban area are likely to make fewer trips than those living in the suburbs.

The second type of analysis focused on Metropolitan Toronto, which constitutes a greater part of the GTA. In this analysis, gravity measures of accessibility were calculated and used along with the socio-economic characteristics to estimate the ordered response model. The results of this analysis in terms of asymptotic t-statistics suggest that accessibility is not a significant input into trip generation decisions of households in the metropolitan area.

The third analysis has two objectives. The first objective is to investigate the direct

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PREFACE

This dissertation consists of three distinct chapters, which have been accepted or submitted for publication. The three are:

Chapter 2:

Agyemang-Duah, K., W. P. Anderson and F. L. Hall (1995) Trip Generation for Shopping Travel. A Paper Presented at the 74th Annual Meeting of the Transportation Research Board, Washington, D.C., and accepted for publication in *Transportation Research Record.*

Chapter 3

Agyemang-Duah, K., F. L. Hall and W. P. Anderson (1995) Analyzing the Effect of Accessibility on Shopping Trip Generation Using an Ordered Response Model, submitted to *Environment and Planning A*.

Chapter 4

Agyemang-Duah, K. and F. L. Hall (1995) Spatial Transferability of an Ordered Response Model, submitted to *Transportation Research A*.

Data preparation, literature review, data analysis and initial drafting of each paper were done by the author of this dissertation. Contributions from the supervisor and Dr. W. P. Anderson (particularly chapter 2) consisted of critiques, discussions and revisions of the drafted papers.

All the three chapters are very close to the submitted papers, with only few minor changes. Given the way the dissertation is presented, there is some duplication among the chapters. In particular, the description of the model in section 2.4 is the same in the latter two chapters (sections 3.4 and 4.2.1 in chapters 3 and 4 respectively). The description of the data is also very similar (sections 2.3, 3.3 and 4.2.2).

CHAPTER 1

INTRODUCTION

1.1 MOTIVATION FOR THE STUDY

Trip generation represents the first stage of the sequential modelling procedure, and determines the overall scale and patterns of trip making. It is thus a very important stage in the transportation planning process. It is, however, plagued with several unresolved issues. Two of these issues are among the four factors that motivated this dissertation: methodological weaknesses in the existing Urban Transportation Modelling System (UTMS) models of trip generation, and the type of variables used in trip generation analysis. The other two factors that motivated this study are the need for effective, low cost transportation planning, and energy and air quality considerations in the transport sector.

First, the methodological issue. The trip making decision is unique in that the outcomes of the trip-making decision have an ordered categorical property. That is, for any given set of factors, each household or individual makes 1, 2, 3, etc trip(s). The existing UTMS trip generation models (mainly regression methods and category analysis) do not, and cannot capture this unique, ordinal nature of trip making decision. Both the regression methods and category analysis treat the number of trips as a continuous dependent variable. But the demand for making trips by any one household or individual is not continuous. Analyzing this travel demand with methods developed for continuous variables ignores the structure of the behavioral situation. The search for an alternative approach that can exploit the ordering of information, and at the same time offers a proper interpretation of the results within the framework of utility maximization therefore becomes very important.

The nature of the variables used in the UTMS trip generation models is another source of motivation for this study. The Institute of Transportation Engineers (ITE) Trip Generation Manual (1987) contains a range of variables used in trip generation analysis. These are mainly socio-economic characteristics of households--household size, income and number of vehicles-- and number of dwelling units, none of which are highly sensitive to policy. Although the manual suggests that location might affect trip generation (p.256), this variable is not found in any of the models used in the manual. The use of location as suggested by ITE is an indirect way to measure the effects of travel costs in time, and/or money and human effort on trip generation, or in general, the characteristics of land use and the transport network. A more direct way to account for these effects in trip generation analysis is to use a measure of accessibility, defined as the ease with which activities may be reached from a given location using a particular transportation system. Accessibility provides one simple, effective measure of the combined characteristics of land use and the transport network.

The absence of accessibility in regression models and category analysis implies the assumption that trip generation is inelastic with respect to this variable. The assumed inelasticity of trip generation rates is a serious drawback in view of the growing concern about the possible effects of land use changes and traffic restraints on trip-making decisions. A major overhaul of the ITE trip generation approaches and of the ITE manual is therefore needed since policy makers should be informed by the best available knowledge about the sensitivity of travel behavior to accessibility. This research is in support of an improved method.

There are two aspects of the low-cost transportation planning. One aspect deals with the cost of increasing capacity to accommodate increasing travel demand. The other aspect relates to the cost of conducting transportation studies. Transportation planning through low-cost methods cannot be overemphasized in the wake of budget cuts. One low-cost method of transportation planning is model transferability, whereby a model formulated and estimated in one context (either time or space) is applied in another context. Although studies of temporal transferability of mode choice models abound in the transportation literature, there are very few spatial transferability studies of trip generation models. The few empirical investigations of spatial transfer studies have been limited to regression models of trip generation. The scarcity of spatial transferability studies of trip generation models is not a good indication of a profession seeking cost-effective methods to carry out its activities. Given the problems of regression models and the scarcity of empirical studies, the need for more studies on spatial transferability of much better trip generation models becomes important.

In the past, transportation plans have sought to increase capacity to meet anticipated increases in travel demand. Recently, however, there has been a departure from this earlier stance due to budget cuts. Research on how land use characteristics and traffic restraints can reduce the amount of travel, through concepts such as neotraditional neighborhood design and travel demand management, has received much attention recently. But the results of past studies (which have used regression models, or performed simple correlation analysis) on the relationship between accessibility and trip frequency are not conclusive. Controversy continues over the degree to which any changes in accessibility levels will induce or reduce trips. More detailed consideration of this issue using better behavioral models that incorporate accessibility as one of the explanatory variables is therefore needed.

Another motivation for the study comes from concerns to reduce energy use in, and air pollution from, the transport sector. Newman and Kenworthy (1990) claim that international data on transportation, land use and energy consumption establish a strong argument for significant changes in travel behavior. A Transportation Research Board (TRB) Special Report (1991) indicates that the need for clean air and energy security calls for a reduction in travel demand, particularly discretionary travel which increased by about 10 percent between 1969 and 1983 in the United States alone. Interestingly, it is discretionary travel that is most amenable to policy manipulations, and the decision that perhaps has the greatest ability to minimize transportation-related energy consumption and pollution. Yet it is the analysis of trip generation for discretionary travel that has benefited the least from recent advances in behavioral travel demand models. Policy analyses of energy use and conservation, and of transport-related air pollution can be jeopardised in the absence of reliable discretionary-trip generation models.

1.2 RESEARCH OBJECTIVES

The importance of an operational, reliable model for trip generation analysis has been emphasized in the previous section. Such a model should overcome the shortcomings in the UTMS trip generation models, incorporate policy-controllable factors and be spatially transferable at little or no cost. The objectives of the research intend to address these issues.

The specific objectives are as follows.

- To address the methodological problems mentioned earlier. This is done by using an ordered response model, a type of discrete choice model that maintains the ordinal nature of the dependent variable in choice situations where there are three or more responses.

- To analyze the effects of geographic location and gravity measures of accessibility on discretionary trips.

- To investigate the spatial transferability of the ordered response model, which is lacking in the published literature.

1.3 FOCUS OF THE RESEARCH

The focus of this research is an analysis of discretionary trip generation in the Greater Toronto Area. Discretionary travel refers to all non-work travel for shopping, social or recreational purposes. Due to lack of data on weekend discretionary trips, only weekday trips are considered. To allow for a better behavioral interpretation of the results, the analysis is limited to weekday, home-based shopping trips.

1.4 ORGANIZATION OF DISSERTATION

The research objectives are addressed in a series of three chapters, accepted or prepared for publication. For this reason, the next three chapters are similar in structure, with some repetitions regarding the model used (sections 2.4, 3.4 and 4.2.1), and to a greater extent the source(s) and variables employed in the analyses (sections 2.3, 3.4 and 4.2.1).

Chapter 2 examines the effect of geographic location of households on weekday, home-based shopping trips in five planning districts within the Greater Toronto Area, which were selected to reflect different types of location. There is an introductory section that emphasizes the relative importance of discretionary travel, and the need to move towards improved trip generation models that are more responsive to locational factors. Of particular importance in this chapter is section 2.4 which describes the analytical method used in this and the subsequent two chapters (3 and 4), and how it overcomes the weaknesses in the UTMS approaches.

An investigation of the effect of accessibility on shopping trip generation is the focus of chapter 3. The principal hypothesis tested is that accessibility is an important factor in determining trip generation rates. The chapter differs from chapter 2 with respect to the study area and the classification of the data. This chapter has additional data for calculating gravity type accessibility indices, a section that critically reviews the concept of accessibility and some past studies on the relationship between accessibility and trip frequency.

Results of spatial transferability of the model are presented in chapter 4. Specifically, the chapter examines the effect of a directly transferred model , and the performance of the scaling parameter updating technique (a procedure to re-estimate the constant terms and 'scalars' in the application context), on transfer effectiveness. The study area in this chapter is the same as in chapter 3 but the classification of the data used in the analysis is different.

The last chapter (5) is a summary of the major findings from the previous three chapters. Major contributions of the research and directions for future research are also outlined in this chapter.

CHAPTER 2

EFFECT OF GEOGRAPHIC LOCATION[1]

2.1 INTRODUCTION

The relative importance of discretionary travel (defined as all non-work travel for shopping, social or recreational purposes) has grown over the years and has also captured the attention of both policy makers and transportation demand modelers. In large metropolitan areas, the ratio of discretionary trips to mandatory trips (work and school) is often greater than one (Hutchinson, 1974). In the Transportation Tomorrow Survey in the Greater Toronto Area in 1986, 68 percent of all household trips were for discretionary purposes. The National Personal Transportation Survey in the United States indicated that the number of discretionary trips grew faster than the number of work trips between 1977 and 1988, with discretionary trips making up three-fourths of all household trips in 1988 (Gordon, Kumar and Richardson, 1988). A recent study in the Regional Municipality of Ottawa-Carleton, Canada showed that shopping, leisure and social trips accounted for more than 52 percent of total trips (IBI Group, 1993).

Despite their sheer volume, discretionary trips have been treated crudely in most operational models. For instance, one way to estimate the number of discretionary trips is by applying a constant factor to the number of work and school (mandatory) trips. Discretionary travel, however, may have different temporal and spatial patterns than mandatory travel.

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[1]This chapter has been accepted for publication in *Transportation Research Record* (1995), with only very minor differences.

Studies on work and school trips focus on maximum peak periods because their purpose is primarily to aid in facility design. The bulk of discretionary trips, however, take place after the morning and evening rush periods when most work trips are over (Prevedouros and Schoffer, 1991). Compared with work and school trips, the number of discretionary trips may be more sensitive to such factors as the cost of travel, accessibility, or the land use pattern, all of which tend to vary spatially within a metropolitan area.

In light of the ongoing shift in the focus of transportation planning from plans to build more infrastructure to plans aimed at modifying travel behavior, the development of better models of discretionary travel should be high on the transportation research agenda. The purpose of this chapter is to start moving towards improved trip generation models for discretionary travel that are more responsive to locational factors.

The rest of the chapter is organized as follows. The next section provides the background for the study. It contains a review of the Urban Transportation Modelling System (UTMS) methods for trip generation analysis and of some past studies on the relationship between trip frequency and the location of trip makers. Section 2.3 deals with the data and the rationale for selecting the locations used. Section 2.4 provides a brief description of the analytical method used and how it addresses the weaknesses identified in the UTMS approaches. Section 2.5 contains discussion of the statistical results and section 2.6 draws conclusions.

2.2 STUDY BACKGROUND

Three things are discussed in this section: current modeling approaches, the nature of explanatory variables currently used for discretionary trip generation, and recent studies that directly address the relationship between trip generation and location.

2.2.1 Modeling Approaches

Regression models and category analysis are the two main methods used for trip generation in the UTMS. Regression models treat the number of trips generated per household (or individual) as a linear function of a set of explanatory variables. Category analysis divides households into categories based on a cross classification of their characteristics, and applies a constant trip generation rate for each category. Both methods have a number of shortcomings.

One problem with the standard regression model is the lack of any built-in upper limit to household trips as the values of explanatory variables such as household size and vehicle ownership increase. There is also the possibility of the regression models predicting negative trips. In an attempt to deal with these problems, the regression model is sometimes given a probabilistic interpretation. Greene (1993) has noted, however, that such a model can predict probabilities greater than one or less than zero.

The difficulty with category analysis is the lack of any effective way to choose the best groupings of household characteristics and hence the best categories. One way is to minimize the standard deviations among the categories. In situations where there are many variables and hence many categories, this involves extensive trial and error. Hutchinson (1974) describes a study by Vandertol using trip data from Hamilton, Ontario, Canada which produced wide margins of error for households within various categories . The error margins range from 10 percent of the average trip rate for one-worker household to 37 percent for four-worker households. (Although the analysis was based on work trip data, it illustrates the problem of defining the best categories.) Another drawback of category analysis is the lack of inferential statistics. In the absence of such measures, there is no way to assess the statistical significance of the explanatory variables in trip generation.

A problem with both models is that they treat the number of trips per household as a continuous dependent variable. One can of course make a statistical defense of this, but in order to develop a behavioral basis for trip generation, the dependent variable must be discrete rather than continuous. One possible solution to this problem is to use the poisson regression model in place of the linear regression model. The poisson regression model has been shown to be appropriate in applications to count data, especially when the count for some observations is small or zero (Guy, 1987). An alternative solution is to use one of the family of discrete choice models, which is based in a probabilistic theory of choice among a finite set of options.

Additionally, there is a definite order to the trip-making decision. If a person makes two trips, that person also necessarily makes one trip. The ordinal nature of the trip-making decision is not, and cannot be, captured by either of the two approaches. The ordered categorical property of the outcomes of trip-making decision makes it imperative to look for an alternative approach that can exploit the ordering of the information. The ordered response model, a type of discrete choice model which maintains the ordinal nature in the dependent variable in situations where there are more than two responses, is therefore the best candidate for trip generation analysis. This approach is adopted in this study.

2.2.2 The Nature of Explanatory Variables

The type of explanatory variables that are usually used in regression models and category analysis are either the socio-economic characteristics of households within a zone (for example, income, car ownership, family size), or if these are not available, the characteristics of the zone itself (for instance, population and employment densities.) Although cost of travel, accessibility or locational factors have been identified as influencing travel decisions, they are generally excluded from operational models. Ortuzar and Willumsen (1990) report that attempts to incorporate accessibility measures into UTMS trip generation models have been unsuccessful, noting that the accessibility index is either non-significant or has the wrong sign in regression models.

A good indication of the range of explanatory variables currently in use is found in the extensive compilation of trip generation rates by the Institute of Transportation Engineers (ITE) in 1987. For generation of shopping trips from residential neighborhoods, for instance, regression models included in the ITE report use household size, the number of vehicles and the number of dwelling units as explanatory variables. (The report does not distinguish between mandatory and discretionary trips so it is assumed that the model is applicable to all types of trip). There is a suggestion in the ITE report that location might affect trip generation, but that is not explicitly followed up in the regression result tables. The ITE noted

> ...dwelling units that were larger in size, more expensive, or farther away from the central business district had a higher trip generation rate per unit than those smaller in size, less expensive, or closer to the CBD. However, other factors, such as geographic location and type of adjacent and nearby

development, also had an effect on the trip generation rates (ITE, 1987, p.256)

The ITE trip generation rates employ adjustment factors for household size, vehicles owned and density (dwelling units per acre). Although density might be correlated with distance from the CBD, the regression models used to produce the ITE trip generation rates do not take explicit account of location within the city.

2.2.3 Past Studies

Very few studies investigate the relationship between observed trip frequency and location within the city. Two studies that do are reviewed here. The first one is a study carried out in the Canadian Regional Municipality of Ottawa-Carleton (IBI Group, 1993). The objective of the study was to explore the observed relationship between transportation, land use and the environment. (The review of the IBI study in this chapter concentrates only on the relationship between trip rates and location within the study area.) The study region was divided into nine distinct areas according to similarity in land use mix and density patterns. The major conclusion is that there are no significant differences in the total trip (both work and non-work) generation rate among the nine areas. The mean daily trips per person range from 2.57 to 3.11 in the nine areas. This conclusion may be questioned on several grounds. For example, the dispersion of trip rates within areas may vary more than the mean number of trips. Additionally, a different conclusion might have been reached if separate analyses were done for mandatory and discretionary trips, since the former is fairly inelastic to locational factors while the latter may not be. Thus the results do not really exclude the possibility of some variation in trip-making behavior over space -- especially for discretionary trips.

Friedman, Gordon and Peers (1994) examined trip frequency in older neighborhoods and the newer suburbs in the San Francisco Bay Area. Using 1980 travel data, the study revealed that the number of total trips per household in the two areas differ significantly: 9 and 11 trips for the older neighborhoods and the suburbs respectively. The study fails to address the following two questions. To what extent does household size correlate with suburban living? Is the difference in trip frequency due to differences in car ownership in the two areas? (This last question is very important because the researchers reported marked differences in mode split for the two areas: 86 percent of trips were by auto in the suburbs against 64 percent in the older neighborhoods.) For these reasons it is impossible to determine whether the results indicate a 'pure' locational effect on trip generation, or simply reflect differences in household characteristics over space.

This review has shown that there are problems with the existing approaches to modeling trip generation and that the results of studies on the trip generation-location relationship are inconclusive. The analysis that follows constitutes an attempt to address some of the methodological problems mentioned above and to provide new empirical evidence on the effect of locational factors on discretionary trip making.

2.3 DATA

The data for the analysis were obtained from the Transportation Tomorrow Survey (TTS) conducted between September and December 1986 by the Joint Program in Transportation

Studies, University of Toronto, and supported by the Ontario Ministry of Transportation. The TTS was a telephone interview survey of a random sample from 1.5 million households in the Greater Toronto Area (GTA), Canada. Completed, usable surveys were obtained for 61,453 households. The GTA is an expanded metropolitan definition that contains three of the twenty-five census metropolitan areas in Canada: Toronto Census Metropolitan Area (CMA) and two contiguous CMAs: Oshawa and Hamilton. For the purpose of the TTS, the GTA was divided into 46 macro-zones.

The survey collected data on households' socio-demographic characteristics and weekday travel patterns. Household characteristics of interest for this analysis are household size, which is the number of persons in the household; the number of household members who are fully employed outside the home, who are employed part-time outside the home, who are working at home, and who are unemployed; the number of children (under 16 years); the number of vehicles and the zone of residence. Unfortunately, the survey does not include information on household income or occupation. Census data on income for 1986 for each zone are available in ten categories. These data cannot be used for detailed analysis however, because an income level for each household is needed. Data on average zonal income which are also available were considered too gross and therefore unsuitable to use in the analysis.

The total number of weekday, home-based shopping trips made by auto and transit is used to calculate household trip generation rates. There was no walk trips for the purpose of shopping in the data set for the five zones. It was decided to include only home-based shopping trips in the analysis in order to allow a more direct behavioral interpretation of the results than would be possible with a broader definition of discretionary trips.

The use of observed trip rates raises the question of latent shopping travel demand. This is particularly so when the data used in the analysis were collected for one weekday, despite the fact that many shopping trips take place at the weekend. The unavailability of weekend shopping trip data, however, is less of a problem given that the goal of this study is to search for improved trip generation models rather than to predict the total number of shopping trips.

The use of weekday, home-based shopping trips raises the question of whether these trips constitute a major proportion of total shopping trips. TTS Report Number 5 provides a table of total (weekdays) shopping trips from each zone. As indicated in Table 2.1, home-based shopping trips are a relatively constant fraction of the total number of weekday shopping trips. Home-based shopping trips as a percentage of all weekday shopping trips vary from 59 to 66 percent in the five zones, confirming the importance of home-based trips and the need to study them. Note however, that shopping trips are defined in the TTS report as all trips that 'have their destination purpose as shop'. It is not clear whether this definition includes trip chains.

The principal hypothesis of this study is that geographic location is an important factor in determining trip generation rates. One simple reason is that location affects people's accessibility, defined as the ease of travel between one point and a set of other points. Ideally, household accessibility measures would have been included in the analysis. However, the data for calculating the accessibility indexes were not readily available. The location of each household in one of five zones within the urban area is therefore used as a proxy for accessibility -- although it may also reflect other spatially variant factors such as 'lifestyle'

Table 2.1 Comparison of weekday, home-based and total shopping trips per household.

Zone	Home-based	Total	%*
1	0.18	0.30	60
2	0.16	0.27	59
3	0.31	0.47	66
4	0.31	0.49	63
5	0.35	0.57	61

*percentage of weekday home-based shopping trips to total number of shopping trips reported.

Table 2.2 Profile of the 5 zones

Indicators	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5
No. of hld*	3210	3723	930	2410	594
Children**	0.46	0.30	0.66	0.79	0.74
Avg. hld size	2.70	2.13	3.22	3.17	3.06
Vehicle/hld	1.11	1.05	1.60	1.76	1.86
Avg. trip***	0.18	0.16	0.31	0.31	0.35

* total number of households interviewed
** average number of household members who were under 16 years
*** average number of home-based shopping trips per weekday
hld = household

differences. Five zones were chosen to reflect very different types of location and accessibility (see Figure 2.1). Two zones (1 and 2) are within the older urban area and are well served with public transportation including buses, trolleys and subways. A third zone is in the inner post-war suburbs, and it is also well served by the transit system. Zones 4 and 5 represent locations that are recently developed suburbs superimposed upon older towns. Each of the last three zones has good expressway access. Zones 4 and 5 have, in addition, a network of rural roads, but relatively poor public transportation service. The total number of households interviewed in the TTS in the five planning zones were 10867. Table 2.2 gives a profile of the five zones.

2.4 THE ORDERED RESPONSE MODEL

The model presented in this section is similar in structure to the probit model developed by McKelvey and Zavoina (1975) for the analysis of Congressional voting on the 1965 Medicare Bill, and by Bhat and Koppelman (1993) for modelling household income and employment, but with different set of assumptions. The ordered response model is an extension of the better known binomial and multinomial logit models. The binomial logit model is used to predict the probability that a categorical variable will take on one of two possible values. In this case it does not matter whether the variable is measured on an ordinal or a nominal scale. The multinomial logit model predicts probabilities for three or more values that a categorical variable can take on. In this case, it is assumed that the variable is measured on a nominal scale. (A common application is the choice among three or more travel modes.) The ordered response model is appropriate when the categorical variable takes on three or more possible

Figure 2.1 The five macro-zones in the Greater Toronto Area

values which are subject to some logical ordering. For example, the categorical variable may be successive levels of educational attainment, ratings from an opinion survey, or employment status (unemployed, part-time employed, and full-time employed.) The number of trips generated from a household is clearly such an ordinally scaled categorical variable.

The ordered response model is based on the definition of an abstract score for each household, which can be interpreted in this application as the utility derived by a household from making shopping trips:

$$U_n = V_n + \varepsilon_n \qquad (2.1)$$

where U_n is the "total" utility that household n derives from making trips, V_n is a systematic or "observed" utility, and ε_n is random component. The V_n is defined as a linear function of attributes of the household:

$$V_n = \beta X_n \qquad (2.2)$$

where β and X_n are respectively a vector of parameters and a vector of household attributes used as independent variables. (A more general specification would include attributes of the choice alternatives in X, however no such attributes are employed in the analysis.) The random component is the part of the utility that is unknown to the researcher. It reflects the idiosyncrasies and tastes that vary randomly for each household together with the effect of omitted variables or measurement errors (Train, 1986). The ordered response model assumes "local" instead of "global" utility maximization. Local utility maximization implies a choice situation where each binary decision consists of whether to accept the current value or "take one more" (Ben-Akiva and Lerman, 1985). The decision maker stops when the first local optimum is reached. Global utility maximization occurs when all alternatives in the choice set are simultaneously considered. The ordered response model was chosen over the ordered generalized extreme value model of Small (1987) which maximizes global utility because of its simple mathematical structure which makes it more convenient for applied analysis.

The model also defines a set of 'cut points' associated with each of the possible outcomes. For example, suppose a household can make 0,1,2,...,J trips, where J is a maximum defined through inspection of the data. Define a cut point λ_1 such that household n will make zero trips if U_n is less than λ_1, or in probabilistic terms

$$P_{n0} = \Pr(\beta X_n + \varepsilon_n \leq \lambda_1) \qquad (2.3a)$$

where P_{n0} is the probability that household n makes zero trips. The probability that the household makes one trip is now defined as the probability that U_n is greater than λ_1 but less than a second cut point λ_2:

$$P_{n1} = \Pr(\lambda_1 < \beta X_n + \varepsilon_n \leq \lambda_2) \qquad (2.3b)$$

or more generally

$$P_{nj} = \Pr(\ \lambda_j < \beta X_n + \varepsilon_n \ \leq \lambda_{j+1}) \tag{2.3c}$$

for j=1,...,J-1 and

$$P_{nJ} = 1 - \Pr(\ \beta X_n + \varepsilon_n \leq \lambda_J) \tag{2.3d}$$

Since it is not possible to observe the values of the random components ε_n, the empirical model is derived by making an assumption about their distribution. The random components are assumed logistically distributed:

$$F(\varepsilon_n) = 1/(1+\exp(-\mu\ \varepsilon_n)) \tag{2.4}$$

where μ is a positive scale parameter which is unobservable, therefore it is assumed that μ=1. Given these assumptions, an explicit form for (2.3a-d) can be written:

$$P_{n0} \quad = 1 / (1 + \exp(\beta X_n \ - \lambda_1)) \tag{2.5a}$$

$$P_{n1} \quad = 1 / (1 + \exp(\beta X_n \ - \lambda_2)) - 1 / (1 + \exp(\beta X_n \ - \lambda_1)) \tag{2.5b}$$

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$$P_{nj} \quad = 1 / (1 + \exp(\beta X_n \ - \lambda_{j+1})) - 1 / (1 + \exp(\beta X_n \ - \lambda_j)) \tag{2.5c}$$

for j=2,3,...,J-1,

$$P_{nJ} = 1 - 1 / (1 + \exp(\beta X_n - \lambda_J)) \quad (2.5d)$$

Estimates of β and $\lambda_1 \ldots \lambda_J$ may be obtained using the maximum likelihood method based on a set of observations (households) making 0, 1,...,or J trips for which the attribute data in X_n are available. An application of the ordered response model in a travel choice situation was the analysis of trip generation behavior of 774 elderly persons in the Washington, D.C. Metropolitan Area (Sheffi, 1979).

The ordered response model has the following advantages over the standard regression model of trip generation. First, the property that choice probabilities are necessarily between zero and one means that in prediction mode, the model cannot forecast negative or infinite trips. The second advantage is that the model predicts the whole distribution of the response levels unlike the standard regression approach which will at best predict the mean of the dependent variable. These advantages of the ordered response model are in addition to what was stated earlier, that the model offers a way to exploit the ordering of information.

2.5 STATISTICAL ANALYSIS

The discussion of statistical analysis covers three main areas. First, a brief discussion of the variables used in the estimation of the model is presented. This is followed by a comparative analysis of alternative utility specification functions. Finally, the estimated results are discussed including tests of the estimated parameters and a comparative analysis to assess the overall fit of the model and to demonstrate the extent of zonal variation in trip-making behavior indicated by the model.

2.5.1 Variables Used

The total number of home based shopping trips over a 24 hour period made by all persons in the household is used in the definition of observed probabilities. ("Trip" as used in the paper is defined as a one-way movement between two places.) If a household is observed to make two trips, the observed probability of making two trips is defined as 1 and the probability of making any other number of trips is defined as 0.

The explanatory variables may be put into two groups: household characteristics and zonal dummy variables. The household characteristics include household size, number of vehicles owned by the household, number of children, and employment status of household members. The household size is expected to be positively correlated with the number of trips since it should influence the level of demand for goods and/or services. The presence of children in the family may have a dual influence on travel. On the one hand, it may lead to some restrictions on time available for shopping. Alternatively, it may be regarded as a scale factor leading to increased shopping trips. (The inclusion of household size controls for this scale effect to some extent, so that one might expect number of children to have a negative effect.) Vehicle ownership dramatically improves mobility and hence one might expect more trips in a household with more cars.

The four categories of employment status- full time, part-time, working at home and unemployed- may exert different time budget constraints on shopping trips. Full-time and to some extent part-time work are expected to have a negative impact on weekday home-based shopping trips. There is no expectation of the nature of effects of working at home on shopping. Two opposing effects of unemployment may be hypothesized. One effect is that the unemployed person has more time and therefore can make more shopping trips. The other hypothesis is that because a person is unemployed, he/she does not have enough money for shopping.

The four zonal dummy variables were introduced into the ordered response model in both additive and interactive manner. Implicit in the use of additive dummy variables is the assumption that zonal effects are independent of the effect of any household characteristic. It is possible that, for example, household size will have a different impact on trip generation in one zone as opposed to another. To test this hypothesis, the zonal dummies were interacted with household size in the model.

2.5.2 Specification and Comparison of Two Utility Functions

Two utility functions were specified, leading to two types of model. In model 1, the effects of household size, number of children and number of vehicles are specified as dummy variables. The utility function in model 2 is a restricted form of model 1 where these same variables were entered in generic form. ('Generic form' means that the explanatory factors are treated as continuous variables. Due to computational difficulties of including large numbers of dummy variables, the employment variables are entered in generic form for both models.)

The two models were estimated in STATA version 3.0, which uses a Newton-Raphson Algorithm. There was some difficulty in estimating model 1 due to very small numbers of observations for household with size greater than six, with five or more children, with more than four vehicles or households making five or more trips. These households were dropped from the data set. The omitted observations constitute only 1.5 percent of the whole data set, leaving 10701 observations for the estimation of the models.

Using a backward stepwise procedure, all the interactive terms were dropped from both models at a significance level of 0.15 which leads to the conclusion that the dummy variables for the zones have an additive, independent effect on trip generation. The variable working at home was also eliminated from the utility functions due to a problem of collinearity with full- and part-time employment. The remaining variables were used to estimate the two models for comparison.

A likelihood ratio test was performed to test the hypothesis that the two models are equal. The test statistic used is $-2(L_2 - L_1)$ which is distributed chi-square. L_1 and L_2 are respectively log-likelihood values for model types 1 and 2. A chi-square value of 32.97 with 10 degrees of freedom was found, which is significant at 0.01, indicating that the two models are unequal. Models 1 and 2 have pseudo R^2 values of 0.0463 and 0.0435 accordingly. (Pseudo R^2 for each model is defined as $1 - L(\beta) / L(c)$, where $L(\beta)$ and $L(c)$ correspond to log-likelihood of a model with all parameters and with only constants respectively). Model 1 was chosen for further analysis because it had a higher log-likelihood value, as evidenced in both the pseudo R^2 and the likelihood ratio test.

2.5.3 Estimated Results

There were two runs of model 1. The first run had all the household size, number of children and vehicles dummy variables. (Household size variable has a minimum value of one and a maximum of six, and number of children and vehicles each ranges from zero to four). Pairwise significance tests were separately performed for the estimated coefficients of household size, and number of children and vehicles dummies. The results showed that the coefficients of all the number of vehicles dummy variables are significantly different from each other. However, household size dummy variables specific to 4 through 6 and the coefficients for children dummy variables specific to 2 through 4 are not significantly different. Dummy variables specific to household size 4 through 6 and number of children 2 through 4 were therefore constrained to be equal and the model was run again.

The estimated parameters, together with their standard errors and z-values (used rather than t-values because of the large sample size) for the second run are presented in Table 2.3. The estimated model is highly significant: a likelihood ratio test of the model against the hypothesis that all the coefficients except the cut points are zero gives a chi-square value of 556 with 16 degrees of freedom.

As one would expect, the dummy variables for household sizes and number of vehicles are significant. The magnitude of the coefficients of these dummies increases with increasing household size and number of vehicles but at a decreasing rate. The implication is that household sizes and number of vehicles have non-linear effects on discretionary trip generation.

Two of the three categories of employment status are negatively weighted. Full- and

Table 2.3 Ordered Response Model Estimates

Variable name	Coefficient	Standard error	z-values
Cut point specific to			
trips=1(λ_1)	2.429	0.119	20.412
trips=2(λ_2)	3.873	0.125	30.984
trips=3(λ_3)	5.690	0.160	35.563
trips=4(λ_4)	7.135	0.252	28.310
Household size (HHS) dummy variables specific to:			
HHS=2	0.578	0.108	5.351
HHS=3	0.921	0.163	5.661
HHS=4	1.174	0.236	4.975
Household members:			
fully employed	-0.567	0.700	-8.095
working part-time	-0.234	0.084	-2.796
unemployed	0.085	0.064	1.319*
Children (CHD) dummy variables specific to:			
CHD=1	-0.354	0.091	-3.879
CHD=2	-0.533	0.112	-4.749
Vehicles (VEH) dummy variables specific to:			
VEH=1	0.587	0.960	6.114
VEH=2	0.885	0.108	8.184
VEH=3	1.170	0.143	8.192
VEH=4	1.524	0.214	7.126
Zone (ZN) dummy variables specific to:			
ZN=2	-0.019	0.074	-0.259*
ZN=3	0.457	0.099	4.614
ZN=4	0.446	0.077	5.768
ZN=5	0.562	0.112	5.010

Summary statistics

Number of observations	10701
Chi-square	556.3
Degree of freedom	16
Prob > chi-square	0.0000
Log likelihood (c)	-6033.79
Log likelihood (β)	-5755.64
Pseudo R^2	0.0461

z-values = coefficient / standard error

All variables except those marked by asterisk (*) are significant at 0.01

Trips=0, HHS=1, CHD=0, VEH=0 and ZN=1 were normalised to zero part-time employment are significant, which may be symptomatic of time budget constraints on weekday, home-based shopping trips. The relatively high negative coefficient of full-time employment is indicative of the severe limitations this variable has on home-based, weekday shopping trips. The effect of unemployment is not statistically significant at 0.1.

The estimated parameters for the two dummy variables for children are negative, and are significant. In interpreting the negative coefficients for the children dummies, one should not lose sight of the fact that the data were collected on the weekdays between September and December when children of school age were at school. Child care responsibilities might have had some time budget effects on trip making.

Zonal dummies specific to zones 3, 4 and 5 are positive and significant, implying that these locations have an effect on trip making relative to the base zone 1. The coefficient of the dummy variable for zone 2 is negative and not statistically significant. (The corresponding value for zone 1 is zero by construction.) Pairwise significance tests based on a quadratic approximation to the likelihood function were performed to determine if the coefficients of these zonal dummy variables are equal. The test results indicate that the differences between the dummy variables for zone pairs 3 - 4, 3 - 5 and 4 - 5 are not significantly different from zero. The test, however, rejects the equality constraint imposed on zone pairs 2 - 3, 2 - 4, and 2 - 5. The implication is that zones 3, 4 and 5 show distinctly different trip-making propensities from zones 1 and 2. There is the possibility that the difference in shopping trip frequency among the zones may be due in part to unobserved income effects. The 1986 average household incomes for zones 1 and 2 are respectively Cdn $32000 and $39000. On the other hand, zones 3, 4 and 5 each has a comparatively higher average household income of approximately Cdn $45000 (Statistics Canada, 1986). However, it is not possible to draw any conclusions about the effect of income on shopping trip fre... .ncy in the absence of adequate, reliable data.

2.5.4 Assessment of Prediction Ability

The following exercise is conducted to illustrate the ability of the model to predict aggregate trip-making propensities, and also to illustrate the contribution of the zonal dummy variables to the predictive ability of the model. Define A_{kj} as the aggregate probability that households in zone k generate j trips, calculated as a relative frequency:

$$A_{kj}=\sum_{n\in Z_k}\frac{P_{nj}}{N_k}$$

where P_{nj} is the probability that household n makes j trips, Z_k is the set of all observations in zone k, and N_k is the number of observations in zone k. A_{kj} is calculated for k =1,2,3,4,5 and j = 0,1,2,3,4. This calculation is done first on the observed number of trips for households in the data and then on the fitted trip making probabilities for the same households based on the estimated model. For the purpose of comparison, these observed and predicted probabilities are presented in the second and third columns of Table 2.4. The results suggest that the model should perform quite well for the purpose of estimating aggregate trip generation from zones.

In order to assess the contribution of the zonal dummy variables to the accuracy of prediction, the model was re-estimated with the zonal dummies omitted from the

Table 2.4 Observed and fitted aggregate probabilities

Trips	Observed	Model with zonal dummy variables	Model without zonal dummy variables
Zone 1			
0	0.8677	0.8672	0.8470
1	0.0938	0.0967	0.1100
2	0.0319	0.0300	0.0355
3	0.0054	0.0047	0.0056
4	0.0013	0.0014	0.0017
Zone 2			
0	0.8726	0.8733	0.8529
1	0.1001	0.0924	0.1060
2	0.0246	0.0285	0.0342
3	0.0022	0.0044	0.0054
4	0.0005	0.0014	0.0017
Zone 3			
0	0.7854	0.7838	0.8206
1	0.1427	0.1525	0.1281
2	0.0619	0.0526	0.0424
3	0.0077	0.0085	0.0068
4	0.0022	0.0026	0.0021
Zone 4			
0	0.7886	0.7866	0.8185
1	0.1441	0.1511	0.1297
2	0.0532	0.0515	0.0428
3	0.0106	0.0083	0.0068
4	0.0034	0.0026	0.0021
Zone 5			
0	0.7435	0.7452	0.8003
1	0.1842	0.1771	0.1418
2	0.0534	0.0639	0.0479
3	0.0120	0.0104	0.0077
4	0.0069	0.0033	0.0024

Columns may not add to one due to rounding error.

specification. Aggregate probabilities calculated based on this model are presented in the fourth column of Table 2.4. There is some zonal variation in these fitted probabilities which comes about due to differences in household characteristics in different parts of the metropolitan area. However, these probabilities do not correspond to the observed probabilities nearly as well as those calculated from the original model. This indicates that, even after controlling for spatial variations in household characteristics, there are differences in trip-making behavior at different locations. These differences may be due to differences in accessibility or to other spatially variant factors.

2.6 CONCLUSIONS

The objective of this paper was to investigate the effects of location on discretionary household trip generation. Data on weekday, home-based shopping trips, socio-economic characteristics and location of households in five widely spaced zones in the Greater Toronto Area were obtained from the TTS. Weekday, home-based shopping trips constitute 59 percent or more of all weekday shopping trips in each zone. An ordered response model was used to analyze the data. Household size, number of vehicles and children, employment status and location of households were included as explanatory variables in the analysis.

The results of the analysis, in terms of the likelihood ratio test of all the explanatory variables, suggest that the estimated model is significant. The z-scores indicate that full- and part-time employment and the dummy variables for household sizes, number of children, number of vehicles, and for zones 3, 4 and 5 produce significant effects on weekday, home-based shopping travel behavior. The significance of the positive coefficients of dummy variables for zones 3, 4 and 5 suggest that suburban living is positively correlated with weekday, home-based shopping trips. A comparison of observed and fitted values of aggregate probabilities of making 0,1,2,3, and 4 trips for households in all five zones indicates that the model has good predictive ability, and that the inclusion of zonal dummy variables contributes significantly to that ability.

Two implications can be identified from this analysis. First, the ordered response model provides a viable methodology for trip generation. The trip-making decision should no longer be treated as a continuous variable or as a dichotomous response, but as a multiple response with a natural order. The other implication is that trip-making behavior appears to be sensitive to location within the metropolitan area, even after controlling for spatial variations in some observed household characteristics, but not household income.

There is a need for further refinements in the application of the ordered response model to discretionary trip generation. The most important is probably the use of accessibility measures in place of spatial dummy variables. Accessibility indexes which take account of travel costs in time, money and human effort and of the spatial distribution of opportunities offer transportation planners a more direct way to measure the effect of location on trip-making behavior.

CHAPTER 3

ACCESSIBILITY AND SHOPPING TRIP GENERATION[2]

3.1 INTRODUCTION

Existing Urban Transportation Modelling System (UTMS) trip generation models such as regression analysis and category analysis express the number of trips as a function of only socio-economic characteristics of the population. These characteristics include household size, income and number of vehicles owned. Such models are, however, not useful with respect to transportation policy application, because transportation policy has little effect on socio-economic variables but more on levels of accessibility. In these models, there is no way to represent changes in trip-making propensity of households over time due to changes in accessibility levels.

The two main arguments in accessibility measures are spatial distribution of activities and travel time or travel cost or a combination of these two. People travel for the purpose of participating in desired activities. Travelling involves costs, either in money, time or both. An increase in travel costs is likely to reduce the propensity to make trips. It is therefore expected that accessibility will have a significant impact on shopping travel.

Policies, especially through land use planning, may be used to influence the transportation network and spatial distribution of opportunities for travel. Other policies such as road pricing may significantly affect the cost of travel. It is expected that policies will have a significant effect on shopping travel behavior.

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[2]This chapter has been submitted in almost the same form to *Environment and Planning A*.

The objective of this chapter is to investigate the importance of accessibility for household shopping travel behavior in Metropolitan Toronto, Canada. Accessibility as used in the study is defined as the ease with which activities may be reached from a given location using a particular transportation system. There are two aspects of this definition. One is the perceived or actual travel time, travel cost or both. It is the travel conditions on the transport network and the mode of travel that determine the travel time or cost. The other aspect is the perceived opportunities. Since travel is a derived demand, any accessibility measures should reflect the spatial distribution of opportunities.

Trip generation is one of the stages in the transportation planning process where transport policy can be directed. The other stages are trip distribution, modal choice and traffic assignment. Models for all three stages contain an element of accessibility: travel time which reflects the quality of the transportation network, and/or the attractiveness of the trip destination. Travel time affects trip distribution, mode split and traffic assignment. Additionally, trip distribution is affected by the attractiveness of trip destinations. These elements can be subjected to various policy controls to influence the distribution of trips and choice of transport mode or route.

An important function of all approaches to travel analysis is to support policy decision-making. But the existing UTMS trip generation models are not policy-oriented. There is currently a need to reassess these modelling approaches . In part this derives from a recognition in transportation planning that increased capacity cannot easily cater for ever increasing rates of traffic growth; and in part from tools of travel demand management, which aim among other things to reduce the amount of travel. This makes it imperative for policy-making to be informed by the best available knowledge about the sensitivity of travel demand to accessibility.

This view has been expressed by Atkins (1977), who suggested that one way to improve the science of modelling in transportation planning is to consider spatial supply price elasticity in the trip generation and modal choice stages. Many researchers in the field have responded favorably to the suggestion for modal choice, as reflected in the numerous demand elasticity studies. The focus has been specifically on transit (for example, Miller and Crowley, 1989), and has lately been extended to route selection (for instance Chan, 1991). This limits the demand elasticity analyses to measuring patronage response to changes in the attributes of the transportation system *after people have decided to travel.*

One decision that has a greater ability to minimize transportation-related energy consumption and pollution and to reduce congestion is the decision of how many trips to make. An analysis of the systematic effects of accessibility on people's travel behavior is a necessary precursor to policies directed toward energy conservation by altering urban land use and transportation system. Quantitative analysis of the association between accessibility and trip generation may also shed some light on the range of behavioral responses that may exist and the complex dynamic process of adaptation that may be implied therein. This may greatly facilitate the design and effective implementation of travel demand management strategies.

The chapter is organised as follows. Section 3.2 contains a discussion of the concept of accessibility. It basically deals with the guidelines for selecting accessibility measures, a review of the methods that have been used to measure accessibility, and some past studies on the relationship between trip frequency and accessibility. A description of the data used in the analysis is presented in section 3.3. Section 3.4 provides a brief description of the analytical method used. This is followed by a discussion of the derivation of accessibility indicators used in section 3.5. Empirical testing of these indicators is done in section 3.6. The variables used to estimate the model, specification of the utility functions used in the model and the statistical results are contained in this section. Lastly, conclusions from the study are presented.

3.2 THE CONCEPT OF ACCESSIBILITY

Three things are discussed in this section: guidelines for selecting accessibility measures suitable to use in trip generation models, a review of the approaches to measure accessibility and some studies that have investigated the relationship between accessibility and trip frequency.

3.2.1 Guidelines for Selecting Accessibility Measures

Accessibility is an intuitive and qualitative concept expressed in terms such as the potential for spatial interaction, the comparative position of a zone among a set of zones (at the aggregate level) or an individual among a group of individuals (at the disaggregate level), or the number of opportunities that can be reached for a given distance or time. Whatever the intended application, the practical value of any accessibility measure depends on the extent to which it reflects travel behavior and perception. It is against this background that three guidelines are defined. The definition of these guidelines draw considerably on the work of

Morris, Dumble and Wigan (1979).

First, the accessibility index should combine in a single, simple measure the relevant characteristics of both the land use and the transport system. Travel is a derived demand, a means to an end. Therefore an accessibility measure should reflect the distribution of opportunities in space as well as the characteristics of the transport system. The latter consists of transport networks and travel modes. It is the characteristics and the efficiency of the networks and travel modes that determine the ease of travel. Accessibility measures should not simply describe the ease of traversing space since such measures only identify the efficiency or deficiency of the transport system, one of the two components of the satisfaction derived from travel. It is equally important that accessibility measures should take account of the probable interest of the trip destination. Defining accessibility on the basis of the spatial distribution of activities and the transport system provides a behavioral foundation to the concept.

The second criterion is that the unit of spatial separation used should be responsive to changes in the transport system. The measures of spatial separation are distance, travel time, travel cost or a combination of these. Measures of spatial interaction that can effectively be used to assess the quality of the network and are relatively easy to measure should be preferred. Two examples of such measures are travel time and travel cost.

The last but not the least guideline is that accessibility measures should be technically feasible, operationally simple and should be easy to understand by the public. In the planning process, technical considerations of operational simplicity and ease of comprehension by both specialists and non-specialists are the two main factors that are looked for when it comes to application of any concept.

3.2.2 Approaches to Measure Accessibility

Three main approaches to measure accessibility are reviewed. These are the distance approach, the gravity method and the cumulative-opportunity approach. All the approaches are based on postulates regarding spatial interaction. It should be stressed that the absence of an explicit micro-economic behavioral construct in these methods of accessibility measurement does not necessarily mean that the approaches have no behavioral content. The rationale is that trip makers will resist costly trips either in terms of money, time or both.

The Distance Approach

The distance approach to measuring accessibility, which is associated with Ingram (1971), focuses on the spatial separation between places. There are two main accessibility indices that are derived from this approach. These are relative accessibility and integral accessibility. Both are aggregate in nature. The relative accessibility is defined as a measure of the effort to overcome spatial separation between two points. The measure is not necessarily reflexive if the link between the two points is unidirectional as in one-way streets.

The integral accessibility is defined as the degree of interconnection between a zone centroid and all other zone centroids in an area (Ingram, 1971):

$$A_{ki} = \sum_{j=1}^{n} t_{ij} \qquad (3.1)$$

where
A_{ki} is the accessibility of zone i derived from the distance method, k
t_{ij} is the network travel distance, time or cost between i and j
n is the number of zones in the study area.

High values of A_{ki} means poor accessibility and vice versa. A characteristic of the integral accessibility measure is that it conceptualizes accessibility as a property of the built environment, the transportation network. Both the relative and integral accessibility measures assume an undifferentiated space with respect to the distribution of opportunities since there is no attractor variable in them. The exclusion of attractor variables such as the number of people employed in retail shopping is justified, according to Ingram (1971), on the grounds that such variables are unequally distributed over space. If, however, travel is a derived demand, then Ingram's reason for excluding attractor variables cannot be justified. It is not only the efficiency of the transportation system that induces travel, but also the satisfaction that will be derived at the trip destination. The effects of spatial variation in the distribution of attractor variables on trip generation is of much interest in transportation planning. Such variables should therefore be included.

The integral accessibility further assumes that origins of all trips are known and all zones in the study area are potential destinations. There are two implications of the origin assumption. One implication is that trips made by any person in the household began at a zone centroid. The other is that all trips are home- or work-based. Thus the accessibility measures that are derived by this approach are all home-based or work-based, but not chained. The convenience of the origin assumption lies in the mathematical simplicity it brings in the calculations and its policy relevance. From a policy view point, one aim of deriving an accessibility index is to establish how accessible certain destinations are to different groups of people living at some known reference 'points'.

The destination assumption means that all zones are potential destinations. There are no preferred destinations. Observed destinations of trips are therefore irrelevant in measuring accessibility. The destination assumption is to prevent the possibility of taking an extant travel pattern as an indicator of preferred ones. Manifest travel behavior does not necessarily reveal the most preferred destinations since the observed travel patterns do not say anything about latent travel.

The Gravity Method

The gravity method is another approach to measure accessibility. In this approach, accessibility is conceived of as the potential opportunities for travel (Koenig, 1980). Putting it another way, accessibility is the ease with which any land use activity can be reached from a given location using a transportation system. The approach postulates that trip makers are attracted to 'larger' destinations (in the sense of more opportunities) for the satisfaction of their trips and that they will avoid more costly trips either in terms of money, time, effort or any combination of these. The gravity measure of accessibility supports the idea that travel conditions and the availability of opportunities cannot be separated when considering the satisfaction derived from trip making. The general form of the gravity method is

$$A_{gi} = \sum_{j=1}^{n} d_j f(t_{ij}) \qquad (3.2a)$$

where
A_{gi} is the accessibility for origin zone i derived from the gravity method, g
n and t_{ij} are defined as before
d_j is a measure of attractiveness in zone j
f(.) is a function, in this case, a travel impedance function.

A_{gi} is "place accessibility" (Pirie, 1979), that is, the access zone i has to other zones. Contrary to the A_{ki} in the distance approach, higher values of A_{gi} mean higher levels of accessibility, thus $f(t_{ij})$ is decreasing in t_{ij}.

The specific form of the function is chosen so as to introduce some behavioral aspect into the accessibility formulation in equation 3.2a. The travel impedance function, $f(t_{ij})$, can be written in several ways. The two most popular formulations are a negative exponent, $t_{ij}^{-\alpha}$ and an exponential function, $\exp(-\alpha t_{ij})$, both a monotonically dec· asing function of t_{ij}. The main difference between the two functions is that the former is unbounded because as t_{ij} approaches zero, $f(t_{ij})$ asymptotically approaches infinity, while the latter has the advantage of being bounded (Kanafani, 1983). Substituting the two travel impedance functions into equation 3.2a gives

$$A_{gi} = \sum_{j=1}^{n} d_j t_{ij}^{-\alpha} \qquad (3.2b)$$

$$A_{gi} = \sum_{j=1}^{n} d_j \exp(-\alpha t_{ij}) \qquad (3.2c)$$

In general terms, equations 3.2b and c are interpreted as the degree to which potential net benefits of travel decline as travel distance, time, cost or a combination of any of these elements increases. The degree to which the net benefits decrease varies with the specific form of travel impedance function.

The α in equations 3.2b and c measures the relationship between interaction patterns and distance or travel time. This relationship is assumed to reflect travellers' perception of the dissatisfaction derived from interacting over different travel distances or time. Hence small values of α indicate that activities can be pursued with minimum perceived travel effort (that is distance or time is less restrictive) while large values indicate that travel distance or time is perceived to be a strong deterrent to interaction or movement. Empirical tests of the power function indicate that the values of α range from 0.5 to 3.0 (Hansen, 1959). Dalvi and Martin (1976) have used 0.2, 0.225 and 0.25 in the exponential function.

In general, the gravity method associates two aspects of utility from trip making with accessibility: the satisfaction provided by the destination opportunities, and travel resistance (disutility) on the transport system. In the case of shopping trips, the destination opportunities may be measured by the shopping floor space of stores, presence of key stores (Robinson and Vickerman, 1976), the total number of people employed in retail shopping activities, or just the number of stores. Weights can be applied to any of these attractive factors. For instance, the floor space can be weighted by the type of stores. The travel impedance can be expressed as generalized travel cost with travel time and out-of-pocket cost among its main components.

The gravity method differs from the distance approach in one respect: the former has attractor variables which are ignored in the latter. The gravity measure of accessibility therefore reflects spatial variation not only in travel impedance but also in destination opportunities. Like the integral accessibility, the gravity approach is aggregate in nature.

An advantage of the gravity approach is that it combines the characteristics of land use and transport system in one simple equation. Besides, it can be easily understood by both experts and the public. A potential difficulty with using the gravity method to measure accessibility is that the gravity measure may be sensitive to zoning system configuration. In general, zone size tends to increase with distance from the city center. This is because the density of urban activities decreases as one moves away from the city center. The zoning system determines the level of spatial description within the city. Hence different zone sizes and zonal configurations are very likely to affect the accessibility measure derived with the gravity approach. Dalvi and Martin (1976) investigated the effect of zoning systems on the values of an accessibility index in inner London. Using a negative exponential form for the impedance function, two measures of attractiveness, total employment and population, and different zone sizes (by aggregating and disaggregating small central area zones), the authors found that the nature of the zoning configuration has a significant effect upon both the absolute and relative values of accessibility. The size of this effect, however, depends on the degree of fineness existing in the initial zoning system. According to the authors, "the greater the fineness of the initial system the less pronounced would be the effect of marginal changes in the zoning configuration". But it is not clear what "fineness" means in their paper.

The Cumulative-opportunity Approach

In this approach, accessibility is conceptualized as the number of opportunities that one could reach for a given travel time or distance. Accessibility therefore increases with longer distance or travel time, and at an increasing rate. The method is given as

$$A_{ci} = \sum_{j \in B} d_j, \qquad \text{subject to } 0 \le t_{ij} \le B_{max} \tag{3.3}$$

where
A_{ci} is the accessibility index for zone i derived from the cumulative-opportunity method, c
$j \in B$ is defined as a set of j zones within the travel band, B
B_{max} is the maximum travel separation band or isodistance
d_j and t_{ij} are defined as before

The cumulative-opportunity approach can be applied at both aggregate and disaggregate levels. An obvious disadvantage of the cumulative-opportunity approach is that the selection of the isodistance or the band is arbitrary. Pirie (1979) has also noted the lack of differentiation between opportunities which are adjacent to the origin *i* and those just within the farthest limit of the travel band.

3.2.3 Choice of an Approach to Measure Accessibility

Overall, accessibility indicators derived from the three approaches are simple in structure and are readily understandable by non-experts. All three approaches could use some measure of spatial separation that is responsive to changes in the transport system, for example, travel time. The distance approach lacks a strong behavioral basis because of its exclusion of any measure of destination attractiveness. The approach measures only the accessibility to the transport system. Given that travel is a means to an end, an approach that measures the accessibility to opportunities via the transport system is preferred. The distance approach is therefore rejected. Although the cumulative-opportunity method has a sound behavioral foundation, the use of an arbitrary isodistance makes it unattractive to use. This leaves the gravity approach which satisfies all the three guidelines discussed earlier, and in addition, does not involve the selection of any arbitrary isodistance. However, the gravity approach does require the choice of a parameter value.

3.2.4 Review of Past Studies

This section presents a review of some empirical works that have investigated the fundamental assumption underlying the use of accessibility measures: that the frequency of participation in activities such as shopping and socializing is influenced by accessibility. Four of these empirical investigations are reviewed here.

Hanson and Schwab Study

In 1987, using data from Uppsala, Sweden, Hanson and Schwab examined the relationship between accessibility and several aspects of travel such as mode use, travel distance and trip frequency. The review of their work here focuses only on trip frequency. To control the effects of the variables known to influence trip generation, notably sex, employment status, and auto availability, these variables were used to stratify the sample into eight subgroups. The subgroups are working male with or without a car, unemployed men with or without a car, employed females who have a car or not, and unemployed women with or without a car. A correlation analysis was performed for discretionary trips. The authors employed a modified cumulative-opportunity accessibility measure which determines the number of opportunities that an individual could reach within a distance of 5 km from home. The specific measure used is

$$A_i = \sum_{n=1}^{10} R_n / 0.5n$$

where
A_i is the accessibility index for individual i
R_n is the number of establishments within the *nth* annulus from the individual's home

It should be noted that dividing R_n by 0.5n makes the approach closer to a gravity model, but with an upper limit of 5 km.

Using this index, a significant, positive correlation was found between accessibility and the number of discretionary trips for all but one male subgroup (non-working men without a car). By contrast, the index was not statistically significant for any female subgroup. The effect of accessibility on shopping trips is statistically significant at the 0.1 level for working men with no car. The major conclusion from the study is that overall, accessibility has relatively little impact on trip frequency.

One good thing done in the study was the calculation of the accessibility index at the disaggregate level, which is in line with the general trend toward disaggregation in travel demand modelling. Nevertheless, there is one major weakness in the study that relates to how the accessibility measure was derived for different subgroups. While it may be convenient and, possibly of practical necessity, it is a grand simplification to use a single accessibility formulation for all the subgroups. In particular, it does not make much sense to use the same maximum travel separation band (5 km) for car and non-car owners. Individuals with cars can reach many more activity sites in a relatively short time over a longer distance than those without a car. Five kilometers may be too long for non-car owners to walk in order to participate in activities. Another shortcoming in the study relates to the distribution of attractor variables within the arbitrary 5 km travel band for all types of discretionary trips. It is unlikely that the spatial distribution of the attractor variables for retail shopping will be the same as for social trips, which may be based on population density. While several convenience stores may be found within a relatively shorter distance, for instance, one may have to travel over a longer distance (more than 5 km) to visit relatives.

Koenig's Work

Koenig (1980) has also investigated the relationship between accessibility and non-work trip rate in five French cities, using a utility maximization approach. The accessibility index used in the study is a modified version of the gravity type at the disaggregate level. Mathematically, the index is

$$A_i^n = \sum d_j^n \exp(-c_{ij}^n / x^n)$$

where
A_i is the accessibility index for origin zone i
d_j is a measure of destination attractiveness
c_{ij} is generalized travel cost
n identifies the individual
x is a parameter associated with the destination choice decision.

The generalized travel cost was expressed as

$c_{ij}^m = k^m t_{ij}^m + 1/V(S_{ij}^m)$

where
t_{ij}^m is the travel time from i to j by mode m
V is the value of time
S_{ij}^m is the monetary cost between i and j by mode m
k is a discomfort coefficient associated with mode m.

Koenig used three categories of age (<30, 30-60, and >60) and two categories of car ownership (possessing a car or not) to stratify the sample into six categories. The accessibility index was calculated for each category. The main finding from this empirical work is that higher levels of accessibility lead to higher trip generation rates, and that this relationship is almost constant over the five cities studied.

Two problems can be identified in the study. One difficulty relates to using the discomfort coefficient, k, to determine the mode with the lowest generalized cost and hence the chosen mode, as Koenig did. The discomfort coefficient is not a good indicator to use to determine the mode with the lowest generalized cost as suggested by Koenig since a 'discomfort mode' does not necessarily mean an 'expensive' mode. Besides, discomfort is a very elusive concept. The other problem in the study has to do with the generalized cost function itself. It is very difficult to comprehend how the travel time was converted into monetary value in the generalized cost function. It appears reasonable to divide the travel time by the value of time. This was, however, not done. It is difficult to interpret the components of the generalized travel cost function.

Robinson and Vickerman's Study

Robinson and Vickerman (1976) used separate money and time costs in a regression model of trip generation in a study of the demand for shopping travel using household data from Sussex. The sample size was 1074 households. The total money cost for zone i (Sc_i) and the total time cost from zone i (St_i) were defined as

$$Sc_i = \sum_{j=1}^{n} C_{ij}, \qquad n \leq 5$$

$$St_i = \sum_{j=1}^{n} H_{ij}, \qquad n \leq 5$$

where n is the number of centers to be reached determined from the data on the basis of frequency of travel to these centers, C_{ij} and H_{ij} are respectively the money and travel time from i to j

An aggregate attraction of n nearest centers was also separately defined and incorporated into the model. The conclusion from the study is that "the suggestion that the incorporation of possible time budget constraints would ... lead to significant variations in trip making was not borne out" (p.272). It is not clear how the total travel time from zone i (St_i) entered into the analysis; only the travel cost variable is found in the estimated results. The specification of the travel cost variable in the regression model should also be questioned. The travel cost was entered into the model in such a way as to have a linear additive effect on shopping travel. But it is reasonable to expect that travel cost will have a non-linear effect. Another problem relates to the use of $n \leq 5$. Although it ($n \leq 5$) was determined from the data based on the frequency of visits, it is not clear whether the frequency of visits was due to only the attractiveness of the shopping centers or travel distance (or travel time or travel cost) or both.

Leake and Huzayyin, 1979

The purpose of the work by these authors was to define a set of accessibility measures suitable for trip generation analysis. Accessibility as used in their work was defined as the ease of travel between two points of a trip. The authors emphasized that it is the efficiency of the transport system that determines the physical meaning of accessibility. Consequently, private transport (auto) accessibility of different places in an area is expressed by the network structure and the travel resistance on the transportation network. No attractor variable was therefore included. Several auto accessibility measures were defined for different trip purposes. The review focuses on the accessibility measure found to be most effective for home-based, non-work trips,

$$D_i = \sum_{j=1}^{n} d_{ij}$$

where D_i is the accessibility of zone i based on travel distance, d_{ij}.

Using a stepwise regression model, the authors concluded that the introduction of an accessibility measure significantly increased the explanatory power of the model. It is, however, not clear if the accessibility effect is positive or negative.

There are two shortcomings found in this study. First, there is a contradiction between the use of d_{ij} and accessibility as defined by the authors to reflect the efficiency of the transportation system. It is hard to conceive how distance could be used to measure the efficiency of the transport system. Travel time, travel cost or convenience is a better measure of the efficiency of the transport system than distance. The rationale for not including an attractor variable in the accessibility is also questioned. Excluding such a variable implies that the authors measured the accessibility to the transport system but not to opportunities via the transport system. Since travel is a derived demand, an accessibility measure which reflects both the spatial distribution of activities and the transport system is preferable to a measure which just describes the efficiency of the transport system.

3.2.5 Summary of Review

The conceptual bases, measurable specifications, strengths and limitations of the distance, gravity and cumulative-opportunity measures of accessibility have been examined. It is clear from the review that accessibility has been defined and measured differently. One thing, however, should be made clear: if travel is generally considered as a derived demand and not an end in itself, it makes sense to define accessibility in a way that reflects the characteristics of both land use and the transport system. The assertion that travel behavior is related to accessibility has not been resolved as seen from the results of the empirical studies reviewed. There is therefore the need for further investigation into the relationship between trip generation and accessibility with better analytical tools and a larger sample size.

3.3 DATA

Three types of data were used: retail shopping opportunities by traffic zone, household socio-demographic characteristics and network data. The last two types were obtained from the Transportation Tomorrow Survey (TTS), conducted between September and December 1986 by the Joint Program in Transportation Studies, University of Toronto, and supported by the Ontario Ministry of Transportation. The TTS was a telephone interview survey of a random sample of the 1.5 million households in the Greater Toronto Area (GTA), Canada. In all, there were 61,453 households from which completed, usable surveys were obtained. There are six municipalities in the GTA, which combine to form three census metropolitan areas (out of the twenty-five in Canada).

Data on the number of people employed in retail shopping by traffic zones were obtained for only one municipality, Metropolitan Toronto, from its Planning Department. Suitable data on retail shopping activities in the other municipalities within the GTA were difficult to obtain. For instance, two municipalities have some employment data from the 1986 Census Place-of-Residence and Place of Work files, but the data are not disaggregated by work type and therefore could not be used. One other municipality has data on the number of people employed in different retail activities, but at the level of traffic zones that are not compatible with the GTA traffic zoning system. The analysis reported in this study is therefore limited to Metropolitan Toronto, which has 55.93 percent of all households interviewed in the GTA. Restricting the analysis to Metropolitan Toronto may reduce the variability in some of the explanatory variables, particularly the accessibility measures as compared to using the whole of the GTA (Figure 2.1). This may reduce the precision with which the affected parameters in the model are estimated.

The TTS collected data on households' socio-demographic characteristics and weekday travel patterns. Household characteristics of interest for this analysis are household size, which is the number of persons in the household; employment status variables, specifically the number of household members who are fully employed outside the home, who are employed part-time outside the home, who are working at home, and are unemployed; the number of children (under 16 years); the number of vehicles and the zone of residence. Unfortunately, the survey does not include information on household income or occupation. Census data on income for 1986 for each planning district are available in ten categories. These data cannot be used for detailed analysis however, because an income level for each household is needed. Data on average income for each planning district, which are also available, were considered too gross and therefore unsuitable to use in the analysis.

The total number of weekday, home-based shopping trips made by auto is used to calculate household trip generation rates. Home-based shopping trips refer to single-leg trips that originated from home for the sole purpose of shopping. The rationale for restricting the analysis to auto users is that data (frequency of a particular type of public transport, operating routes, length of route, the number of public transport modes serving a particular zone, etc) were not readily available to calculate accessibility measures for public transport which is used by households without a car. Using accessibility measures based on the characteristics of private transport for non-car owners will therefore confound the results. Walk trips for the purpose of shopping were also eliminated from the data set because there were very few of them, less than 0.05 percent. It was decided to include only home-based shopping trips in the analysis in order to allow a more direct behavioral interpretation of the results than would be possible with a broader definition of discretionary trips.

Inter-zonal travel times on the network were also obtained from the TTS. Link travel times were estimated by the TTS as follows. The road network for auto was created from data provided by the Planning Department of Metropolitan Toronto. The road information was initially assembled with no reference to any particular traffic zoning system. An automated procedure, based on the TTS data, was then used to obtain likely zone centroid positions for the 1979 TARMS traffic zones, which are 400 in number. (TARMS is an acronym for Toronto and Region Modelling Studies.) Centroid connectors were subsequently generated and checked manually for these traffic zones. Inter-zonal travel times were obtained by the TTS for all the 400 zone centroids using link travel times modified to reflect traffic volumes:

$$L_t = (\text{link length} / \text{free flow speed}) * (1 + (v/c)^4)$$

where L_t is the link travel time and v/c is the volume to capacity ratio on the link. The traffic volume used was obtained from a capacity-restrained traffic assignment. A free flow speed of 50 km/h (which is the speed limit within the metropolitan area unless otherwise posted) was used for all arterials with frequent signals and/or stop signs. For the major arterials, the posted speed limit within the metropolitan area was used.

An important omission in the TTS network data is intra-zonal travel times. To approximate these values, the following were done. The intra-zonal travel distance (in kilometers) was first calculated and subsequently converted into travel times using off-peak travel speed limit of 50 km/h. Three assumptions were made: each TARMS traffic zone is square in shape; the farthest point a person can travel within a traffic zone is half of the vertical/horizontal or diagonal distance; and all zones are identical in size. The steps involved in determining an intra-zonal distance are as follows. The average area of a traffic zone was determined by dividing the total land area of Metropolitan Toronto by the number of traffic zones. The length/width of a traffic zone was obtained by taking the square root of the average area of a traffic zone. Pythagoras Theorem was then used to find the maximum (diagonal) distance within a traffic zone. By the second assumption, the intra-zonal travel distance (I_d) is the average of the midpoints of the diagonal (g) and the width/length (w):

$$I_d = (g + w) / 2$$

The estimated intra-zonal travel time was added to the inter-zonal travel times matrix to obtain the diagonal elements.

3.4 ANALYTICAL METHOD

The analytical method presented here is the same as the one used in an earlier paper (Agyemang-Duah *et al*, 1995[3]). The model used is an ordered response model, which is similar in structure to the probit model developed by McKelvey and Zavoina (1975) for the analysis of Congressional voting on the 1965 Medicare Bill, and by Bhat and Koppelman

[3]That paper is chapter 2 of this dissertation. This section repeats much of section 2.4 of the dissertation

(1993) for modelling household income and employment, but with a different set of assumptions. The ordered response model is an extension of the better known binomial and multinomial logit models. The binomial logit model can be used to predict the probability that a categorical variable will take on one of two possible values. In the binomial case it does not matter whether the variable is measured on an ordinal or a nominal scale. The multinomial logit model predicts probabilities for three or more values of a categorical variable. (A common application is the choice among three or more travel modes.) The ordered response model is appropriate when the categorical variable takes on three or more possible values which are subject to some logical ordering. For example, the categorical variable may be successive levels of educational attainment, or ratings from an opinion survey. The number of trips generated from a household is clearly such an ordinally scaled categorical variable.

The ordered response model is based on the definition of an abstract score for each household, which can be interpreted in this application as the utility derived by a household from making shopping trips:

$$U_n = V_n + \varepsilon_n \qquad (3.4)$$

where U_n is the "total" utility that household n derives from making trips, V_n is a systematic or "observed" utility, and ε_n is a random component. V_n is defined as a linear function of attributes of the household:

$$V_n = \beta X_n \qquad (3.5)$$

where β and X_n are respectively a vector of parameters and a vector of household attributes used as independent variables. (A more general specification would include attributes of the choice alternatives in X, however no such attributes are employed in our analysis because the alternatives are simply the number of trips made.) The random component is the part of the utility that is unknown to the researcher. It reflects the idiosyncrasies and tastes that vary randomly for each household together with the effect of omitted variables or measurement errors (Train, 1986). The ordered response model assumes "local" instead of "global" utility maximization. Local utility maximization implies a choice situation where each binary decision consists of whether to accept the current value or "take one more" (Ben-Akiva and Lerman, 1985). The decision maker stops when the first local optimum is reached. Global utility maximization occurs when all alternatives in the choice set are simultaneously considered. The ordered response model was chosen over the ordered generalized extreme value model of Small (1987) which maximizes global utility because of its simple mathematical structure which makes it more convenient for applied analysis.

There are three advantages that made the ordered response model preferable to the multinomial logit and the standard regression analysis. Unlike the regression method, the ordered response model cannot forecast negative or infinite trips. Besides, the ordered response model predicts the whole distribution of the dependent variable just like the multinomial logit, but the regression method will at best predict the mean of the dependent variable. Lastly, the ordered response model offers a more efficient way to exploit the ordinal nature of the dependent variable. Although a multinomial logit model could be used to exploit the ordering of information in the dependent variable, it would mean specifying all the explanatory variables as alternative specific, a more arduous task.

The model defines a set of 'cut points' associated with each of the possible outcomes. For example, suppose a household can make 0,1,2,...,J trips, where J is a maximum defined through inspection of the data. Define a cut point λ_1 such that household n will make zero trips if U_n is less than λ_1, or in probabilistic terms

$$P_{n0} = \Pr(\beta X_n + \varepsilon_n \leq \lambda_1) \tag{3.6a}$$

where P_{n0} is the probability that household n makes zero trips. The probability that the household makes one trip is now defined as the probability that U_n is greater than λ_1 but less than a second cut point λ_2:

$$P_{n1} = \Pr(\lambda_1 < \beta X_n + \varepsilon_n \leq \lambda_2) \tag{3.6b}$$

or more generally

$$P_{nj} = \Pr(\lambda_j < \beta X_n + \varepsilon_n \leq \lambda_{j+1}) \tag{3.6c}$$

for j=1,...,J-1 and

$$P_{nJ} = 1 - \Pr(\beta X_n + \varepsilon_n \leq \lambda_J) \tag{3.6d}$$

Since it is not possible to observe the values of the random components ε_n, the empirical model is derived by making an assumption about their distribution. The random components are assumed logistically distributed:

$$F(\varepsilon_n) = 1/(1+\exp(-\mu\,\varepsilon_n)) \tag{3.7}$$

where μ is a positive scale parameter which is unobservable, therefore it is assumed that μ=1. Given these assumptions, an explicit form for (3.6a-d) can be written:

$$P_{n0} = 1 / (1 + \exp(\beta X_n - \lambda_1)) \tag{3.8a}$$

$$P_{n1} = 1 / (1 + \exp(\beta X_n - \lambda_2)) - 1 / (1 + \exp(\beta X_n - \lambda_1)) \tag{3.8b}$$

.

.

$$P_{nj} = 1 / (1 + \exp(\beta X_n - \lambda_{j+1})) - 1 / (1 + \exp(\beta X_n - \lambda_j)) \tag{3.8c}$$

for j=2,3,...,J-1,

$$P_{nJ} = 1 - 1 / (1 + \exp(\beta X_n - \lambda_J)) \tag{3.8d}$$

Estimates of β and $\lambda_1 \ldots \lambda_J$ may be obtained using the maximum likelihood method based on a set of observations (households) making 0, 1,...,or J trips for which the attribute data in

X_n are available. An application of the ordered response model in travel choice situation was the analysis of trip generation behavior of 774 elderly persons in the Washington, D.C. Metropolitan Area (Sheffi, 1979).

3.5 CALCULATING ACCESSIBILITY INDICES

The gravity approach was used to calculate seven accessibility indices that were used in the analysis. The indices measure the accessibility of a traffic zone relative to all other traffic zones. The traffic zone of each household is known in the TTS data. The zonal accessibility indices were assigned to all households in that particular traffic zone. Two functional forms of the impedance function were used, an inverse power function ($\sum_j d_j t_{ij}^{-\alpha}$) and a negative exponential function ($\sum_j d_j \exp(-\alpha t_{ij})$). The shopping attractiveness variable used is the number of people employed in retailing in each TARMS zone.

Ideally, an iterative calibration process should be used to determine the optimal values of the parameter, α, associated with the travel time. This was not done because it would have been too time consuming. Instead, a 'graphical' approach was used to select seven different parameter values, three for the power function and four for the exponential function. In selecting these values, the objective was to cover a range of values and functional forms for the travel impedance function, $f(t_{ij})$. The selected values for α are 1.5, 2.0 and 3.0 for the power function, and 0.14, 0.25. 0.5 and 1.0 for the exponential function. These values represent different levels of perception of travel time as a deterrent to trip generation. Within the context of the ordered response model, α may be interpreted as a measure of marginal disutility of travel. Figures 3.1a and b are the graphical presentations of the effects of these

Figure 3.1a Power function of travel impedance, t_{ij}^{α}

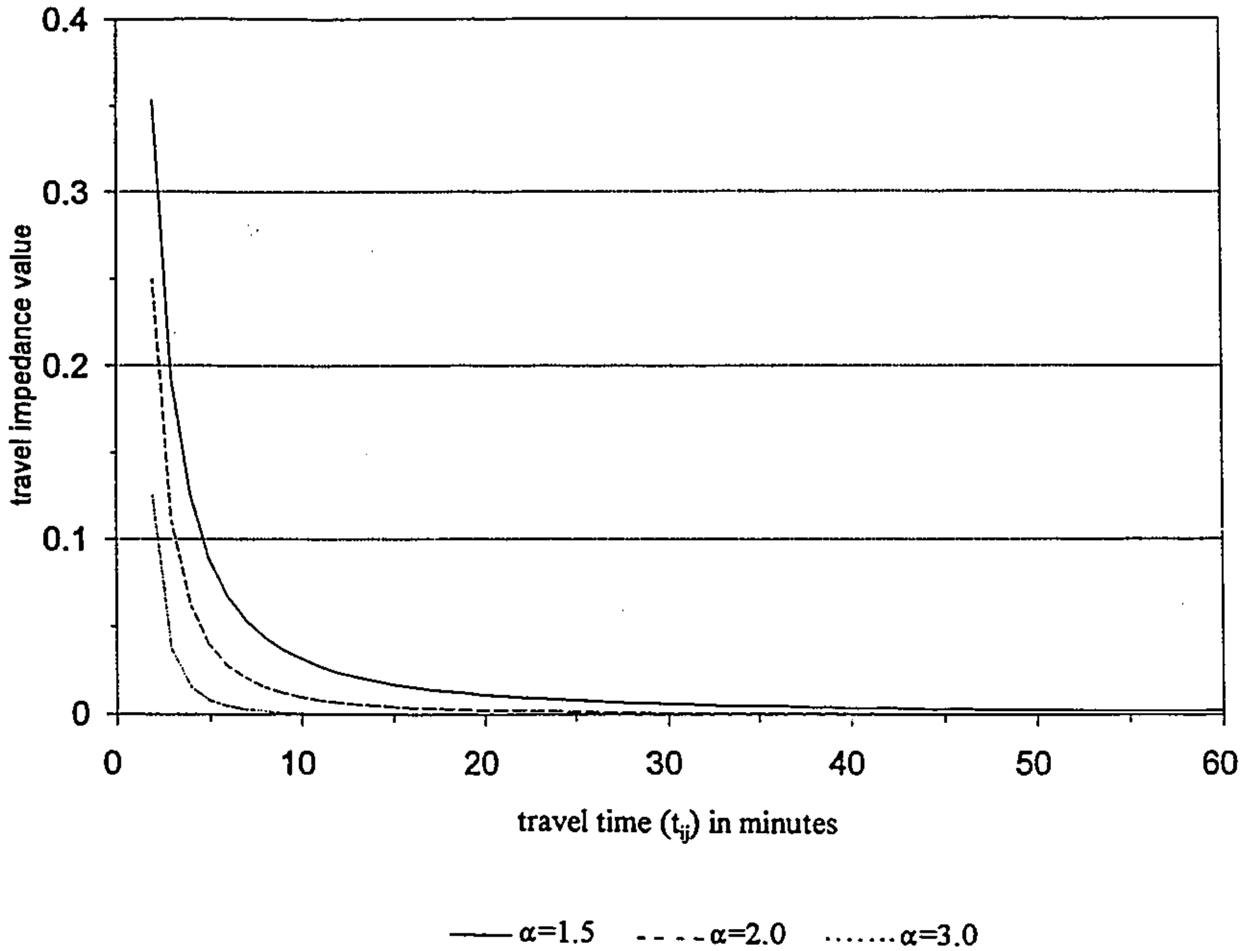
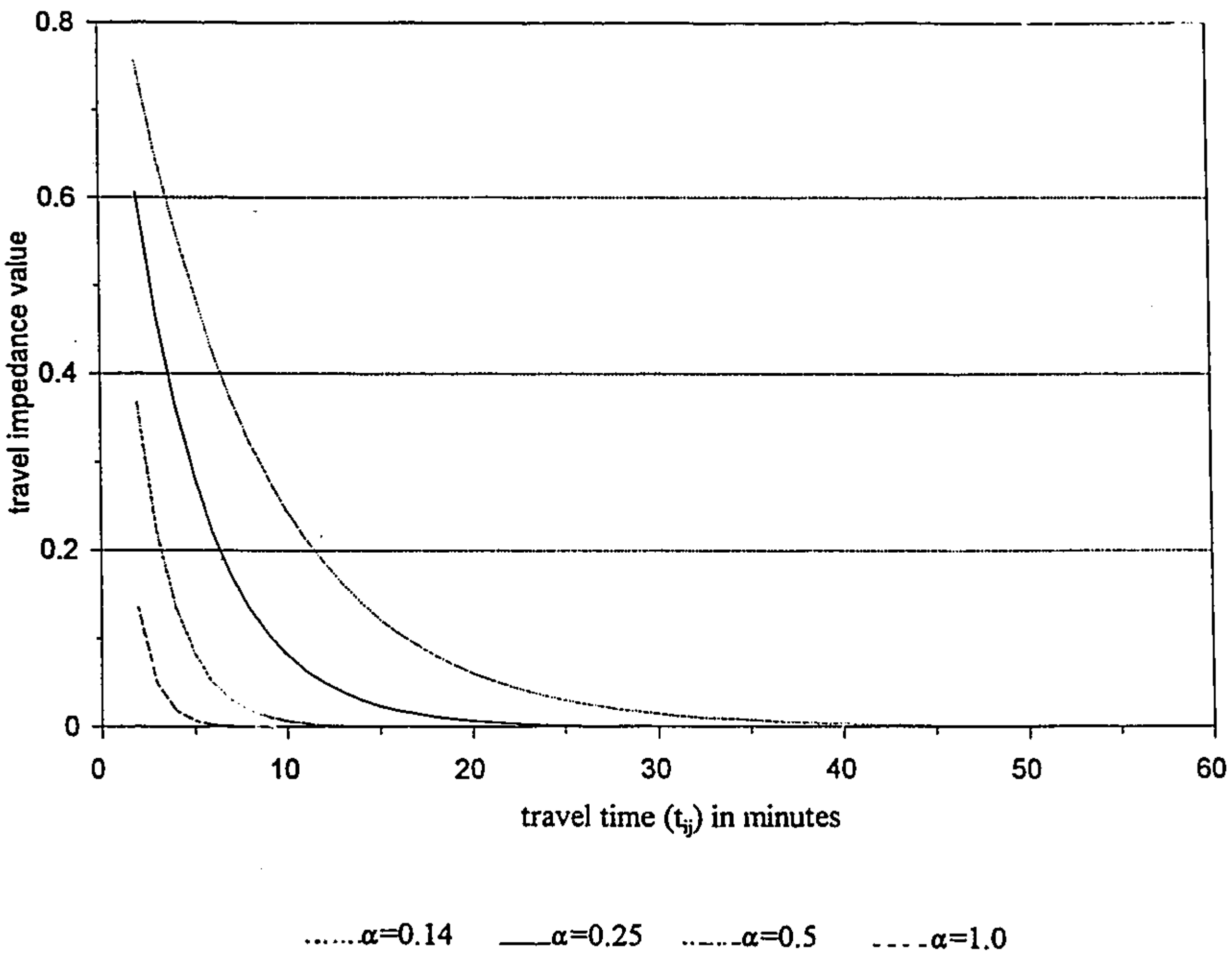


Figure 3.1b Exponential function of travel impedance, exp($-\alpha t_{ij}$)



values. In plotting these graphs, a minimum travel time of two minutes (which is almost the same as the calculated intra-zonal travel time of 1.9 minutes) and a maximum of sixty minutes (which represents the travel time from one extreme point to another when moving diagonally within the metropolitan area at the average speed of 50 km/h) were used.

There were two issues that had to be resolved before calculating the accessibility indices. One issue relates to the fact that within an open system like Metropolitan Toronto, there is always the possibility that some trips that originated within the metropolitan area were destined outside it. For such trips, the shopping opportunities variable would have to be calculated differently, which may be inconsistent with the shopping opportunities for trips that have their destinations within the system. A frequency distribution of destinations of shopping trips was therefore determined from the data. The results indicated that destinations of all shopping trips from fourteen planning districts out of a total of 16 planning districts were within Metropolitan Toronto (Figure 3.2). For the remaining two planning districts, 99.8 percent of the shopping trips ended within Metropolitan Toronto. No harm is done to the analysis by restricting destinations to Metropolitan Toronto, which is necessary because of the data limitations.

3.6 EMPIRICAL TESTING OF THE INDICES

The principal hypothesis of this study is that accessibility is an important factor in determining trip generation rates. To test this hypothesis, the data set for the whole of the metropolitan area was used. First, a brief discussion of the variables used to estimate the model is presented. This is followed by specification of the utility functions and a discussion of the

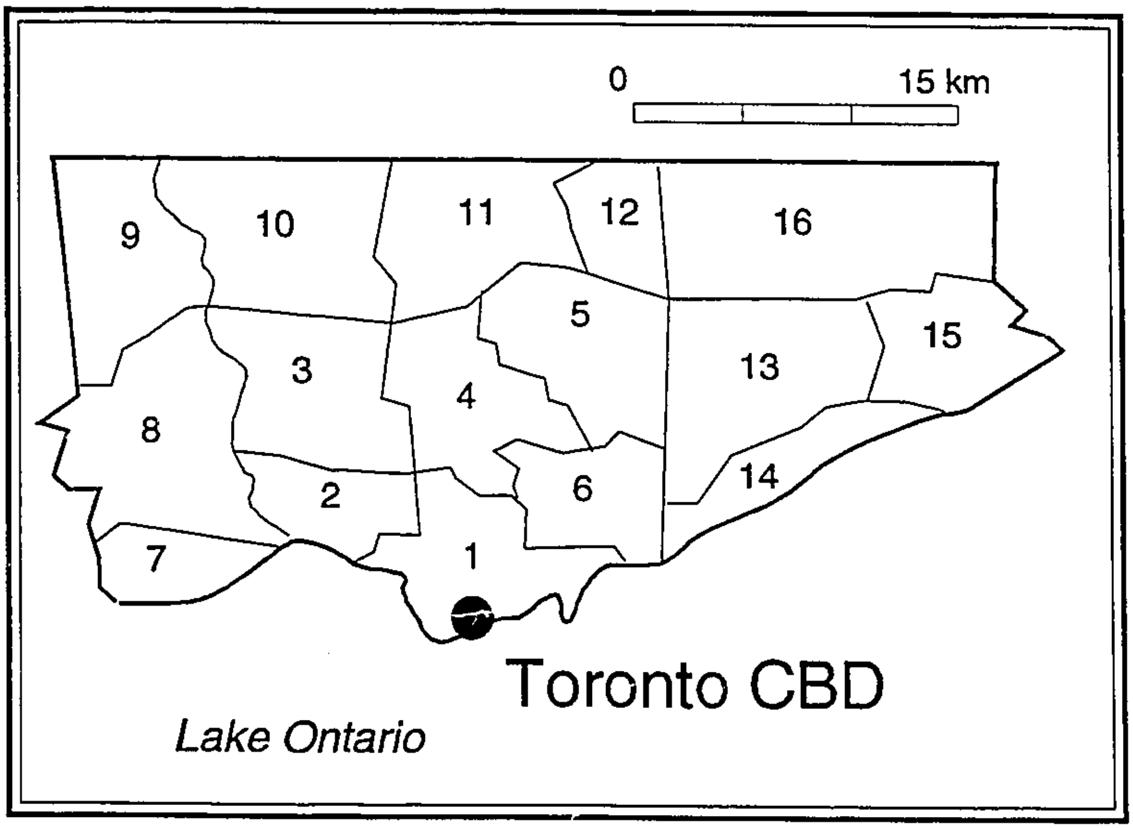


Figure 3.2. The sixteen planning districts in Metropolitian Toronto.

estimated results.

3.6.1 Variables Used

The total number of home-based shopping trips over a 24 hour period made by all persons in the household is used in the definition of observed probabilities. ("Trip" as used in the chapter is defined as a one-way movement between two places.) If a household is observed to make two trips, the observed probability for making two trips is defined as 1 and the probability of making any other number of trips is defined as 0.

The explanatory variables may be put into two groups: socio-economic variables and spatial factors comprising accessibility and planning district dummy variables. The socio-economic variables used are the same as in an earlier paper (Agyemang-Duah *et al*, 1995). Household characteristics include household size, number of vehicles owned by the household, number of children, and employment status of household members. The household size is expected to be positively correlated with the number of trips since it should influence the level of demand for goods and/or services. The presence of children in the family may have a dual influence on travel. On the one hand, it may lead to some restrictions on time available for shopping. Alternatively, it may be regarded as a scale factor leading to increased shopping trips. (The inclusion of household size controls for this scale effect to some extent, so that one might expect the number of children to have a negative effect.) Vehicle ownership dramatically improves mobility and hence one might expect more trips in a household with more cars.

The four categories of employment status -- full-time, part-time, working at home and unemployed -- may exert different time budget constraints on shopping trips. Full-time and, to some extent, part-time work are expected to have a negative impact on weekday home-based shopping trips. There is no expectation of the nature of working at home on shopping. Two opposing effects of unemployment may be hypothesized. One effect is that the unemployed person has more time and therefore can make more shopping trips. The other hypothesis is that because a person is unemployed, he/she does not have enough money for shopping.

The explanatory variables consist of generic and dummy variables. (A generic variable is one that is treated as a continuous variable.) Computationally, it was difficult to include a large number of dummy variables. Hence the employment variables were entered in generic form. The total number of observations in the metropolitan area was 27,341. Because of the small number of observations for household size greater than five, with more than four children, and with five or more vehicles, these households were deleted from the data set. The deleted observations constitute about 1.2 percent of the data set, leaving 27,012 observations for analysis. Table 3.1 summarizes the socio-economic characteristics and trip information of the remaining sample households.

Since the focus of the chapter is on accessibility, the descriptive statistics for all the accessibility indices are separated from those for socio-economic characteristics and trip information. The mean and standard deviation of the indices are given in Table 3.2. For easy comparison, the coefficient of variation for each one is also given.

Table 3.1 Profile of the sample households in Metropolitan Toronto

Variable	Mean	Std. Dev.
Household size	1.84	0.36
Full employment	1.38	0.89
Part-time employment	0.20	0.48
Work-at-home	0.04	0.21
Unemployment	1.15	1.12
Number of children	0.46	0.81
Number of vehicles	1.51	0.70
Number of trips	0.24	0.59

Table 3.2 Descriptive statistics of accessibility indices

Index*	Mean	Std. Dev.	CV
A1	4207.01	1037.08	24.65
A2	1677.09	605.28	36.09
A3	418.08	260.32	62.27
A4	24249.74	5125.24	21.14
A5	9124.27	2801.17	30.70
A6	2091.17	990.66	47.37
A7	362.22	249.85	68.98

*A1, A2 and A3 are the accessibility indices calculated using the power function (equation 3.2b) with alpha equals -1.5, -2.0 and -3.0 respectively. A4 to A7 are the indices derived from the exponential function (equation 3.2c) with alpha equals -0.14, -0.25, -0.5 and -1.0 accordingly. CV is the coefficient of variation : standard deviation (std. dev.) / mean * 100

3.6.2 Specification of Utility Functions

The model described in section 3.4 was estimated in STATA version 3.0, which uses a Newton-Raphson algorithm. Three utility functions were estimated. In all the estimations, no restrictions were placed on the admission of variables into the models. In the first model, called 'location-specified' (LS) model, the estimation was based on households' socio-economic attributes and the planning district dummy variables; no accessibility index was admitted. The second model, called 'accessibility-specified' (AS) model has all the socio-economic characteristics as in the LS model as well as an accessibility index. No planning district dummy variable was allowed in the AS model. The AS model consists of seven submodels, one for each accessibility index. To determine the relationship between accessibility and planning district dummy variables, a third model labelled as 'location-accessibility-specified' (LAS) model was estimated on the socio-economic factors, the planning district dummy variables and each accessibility index. The initial specifications of all the three models are presented in Table 3.3.

Since the estimated coefficients of the dummy variables are interpreted relative to a base case, there should be D-1 dummy variables. The dummy variables specific to household size of one person, zero children and one vehicle were normalized to zero. For the same reason, the cut point specific to zero trips was also normalized to zero. There were 15 (16-1) district dummy variables.

3.6.3 Initial Analysis

There were two estimations of all the three models on the data set for Metropolitan Toronto.

In the first estimation, the specifications as shown in Table 3.3 were used. A visual inspection of the estimated coefficients for household size dummy variables suggested that some of the coefficients may not be statistically different from each other. Similar observations were also made for the number of children. Consequently, log-likelihood ratio tests were separately performed for these variables to determine if they should be constrained to be equal. The test was carried out as follows.

Suppose that a test is to be performed on the equality of two coefficients, $\beta_3 = \beta_4$. A base model is estimated where X_3 and X_4 enter as separate variables. Letting Y be the index of the ordered response, the base model is

$$Y = \beta_1X_1 + \beta_2X_2 + \beta_3X_3 + \beta_4X_4 + ...$$

If $X_3 = X_4$, this can be written as

$$Y = \beta_1X_1 + \beta_2X_2 + \beta_3(X_3 + X_4) + ...$$

which is called a constrained model. To estimate the constrained model, a variable equal to the sum of X_3 and X_4 is created and the model is re-estimated including this new variable. This is followed by a log-likelihood ratio test based on the log-likelihood of the base (L_b) and the constrained (L_c) models:

$$\chi^2 = -2(L_c - L_b).$$

Table 3.3 Specification of the utility function for the three models

Explanatory variable	Model type LS	AS	LAS
Household size (HS) dummy variables specific to			
HS = 2	x	x	x
HS = 3	x	x	x
HS = 4	x	x	x
HS = 5	x	x	x
Number of household members:			
fully employed	x	x	x
working part-time	x	x	x
working at home	x	x	x
unemployed	x	x	x
Children (CH) dummy variables specific to			
CH = 1	x	x	x
CH = 2	x	x	x
CH = 3	x	x	x
CH = 4	x	x	x
Vehicle (VH) dummy variables specific to			
VH = 2	x	x	x
VH = 3	x	x	x
VH = 4	x	x	x
Planning district dummy variables	x	-	x
Accessibility index	-	x	x

x = variable included in the model - = variable excluded from the model

Note: the cut points are not shown in the table since they depend on the maximum number of trips in the data set

The test is distributed as χ^2 with degrees of freedom equal to the difference in the number of estimated parameters of the base and the constrained models (Ben-Akiva and Lerman, 1985). If the test statistic is significant at a specified confidence level, the equality constraint imposed on the two coefficients is rejected.

The test results, at the confidence level of 0.95, indicate that the household size dummy variables specific to 2 through 6 are not significantly different from one another. Likewise the dummy variables specific to 3 and 4 children are not different. In the case of the vehicle dummy variables, however, all the estimated coefficients were statistically different from each other. The models were therefore re-estimated with one dummy variable for household size 2 through 6, and another for 3 or 4 children.

3.6.4 Results of the Revised Models

The estimated results of the revised models are discussed in this section. The discussion is broken down into the effects of the socio-economic variables; the impact of the planning district dummy variables, and accessibility; and an investigation into the relative strength of the planning district dummy variables and the accessibility indices. The estimated results for the revised LS and one AS models are presented in Tables 3.4 and 3.5. (Since all the accessibility measures operate in pretty much the same way, only one of the AS models is presented.) A likelihood ratio test of the null hypothesis that each of the estimated coefficients is equal to zero is rejected in all models at a significance level of 0.05.

Table 3.4 Estimated results from the revised LS model

Variable	Coefficient	Std. Error	z-value
Cut point specific to			
trip = 1	2.57228	0.10974	23.440
trip = 2	3.91198	0.11210	34.897
trip = 3	5.90941	0.12870	45.916
trip = 4	7.21608	0.16997	42.455
trip = 5	8.99421	0.33458	26.882
trip = 6	9.91096	0.51180	19.365
trip = 7	10.60422	0.71550	14.821
Household size (HS) dummy variable specific to			
HS > 1	0.53182	0.06432	8.268
Household members			
fully employed	-0.32289	0.02640	-12.231
working part-time	0.03568	0.03580	0.997
working at home	0.12233	0.07385	1.656
unemployed	0.31196	0.02452	12.723
Children (CH) dummy variable specific to			
CH = 1	-0.42833	0.05406	-7.923
CH = 2	-0.58693	0.06569	-8.935
CH = 3 or 4	-0.86218	0.11022	-7.822
Vehicle (VH) dummy variable specific to			
VH = 2	0.25367	0.03794	6.686
VH = 3	0.40967	0.06763	6.058
VH = 4	0.77240	0.11457	6.742
Planning district (PD) dummy variable specific to			
PD = 2	0.08415	0.12596	0.668
PD = 3	0.38502	0.11623	3.313
PD = 4	0.39637	0.11392	3.479
PD = 5	0.67551	0.12069	5.597
PD = 6	0.48730	0.11595	4.203
PD = 7	0.55753	0.14756	3.778
PD = 8	0.88179	0.11052	7.979
PD = 9	0.93032	0.13109	7.097
PD = 10	0.49032	0.12280	3.993
PD = 11	0.70303	0.11547	6.088
PD = 12	0.72076	0.12825	5.620
PD = 13	0.82173	0.11255	7.301
PD = 14	0.87707	0.13294	6.597
PD = 15	0.82751	0.13326	6.210
PD = 16	0.68527	0.11475	5.972

Summary statistics	
Number of observations	27012
Chi-square	1321
Degree of freedom	26
Prob > chi-square	0.0000
Log likelihood at constant	-16238
Log likelihood at convergence	-15578
Pseudo R^2	0.0407

123 not significant at 0.05 level

note: a two-tailed t-test was performed for working part-time, working at home and unemployed variables, and all the planning district dummy variables

Table 3.5 Estimated results from the revised AS model

Variable	Coefficient	Std. Error	z-value
Cut point specific to			
trip = 1	1.78119	0.06347	28.063
trip = 2	3.11549	0.06708	46.444
trip = 3	5.10990	0.09204	55.518
trip = 4	6.41622	0.14421	44.492
trip = 5	8.19414	0.32225	25.428
trip = 6	9.11086	0.50383	18.083
trip = 7	9.80410	0.70982	13.812
Household size (HS) dummy variable specific to			
HS > 1	0.56783	0.06405	8.865
Household members			
fully employed	-0.33443	0.02609	-12.818
working part-time	0.03735	0.03564	1.048
working at home	0.10351	0.07367	1.405
unemployed	0.30982	0.02431	12.745
Children (CH) dummy variable specific to			
CH = 1	-0.43192	0.05378	-8.031
CH = 2	-0.58244	0.06536	-8.911
CH = 3 or 4	-0.87522	0.10971	-7.978
Vehicle (VH) dummy variable specific to			
VH = 2	0.29526	0.03752	7.869
VH = 3	0.47346	0.06709	7.057
VH = 4	0.84653	0.11419	7.413
Accessibility (A3)	-0.00056	0.00008	-7.000

Summary statistics	
Number of observations	27012
Chi-square	1166
Degree of freedom	12
Prob > chi-square	0
Log likelihood at constant	-16238
Log likelihood at convergence	-15655
Pseudo R^2	0.0359

123 not significant at 0.05 level

note: a two-tailed t-test was performed for working part-time, working at home and unemployed variables

Socio-economic variables

A summary of the effects of the socio-economic variables in the models is as follows. The LS and AS models indicate that the household size dummy specific to 2 through 6, the number of persons unemployed and all the vehicle dummy variables are positive and are significant. The coefficients on the dummy variables for the number of vehicles show that the effect of increasing the number of vehicles is non-linear, which is good support for using the dummy variable approach instead of seeking one coefficient for a generic variable. The two models also show that all the children dummy variables and the number of persons employed full-time have negative coefficients and are statistically significant. The children dummy variables also have a non-linear effect on trip generation. The work at home and part-time variables have positive estimated coefficients but both are not significant. The unemployment variable is positive and significant in both the LS and AS models. In general, the results accord closely with those obtained in an earlier analysis (Agyemang-Duah *et al*, 1995).

Planning district dummy variables

The estimated coefficients for the planning districts dummy variables specific to core planning districts 3 through 16 from the LS model (Table 3.4) are positive and are all statistically significant. The coefficient of the planning district dummy variable specific to planning district 2 is positive, but not significant. The coefficient for planning district 1 is zero by construction. The non-significance of the coefficient of the dummy variable specific to planning district 2 implies that this particular planning district is not distinctly different from planning district 1 in terms of its impact on trip-making propensities.

Pairwise significance tests using the likelihood ratio method described in section 3.6.3 were performed to determine if the coefficients of the planning district dummy variables are equal. The major findings are as follows. Planning district 2 is significantly different from all other planning districts (3 to 16). With the exception of few planning districts pairs (5-7, 6-7, 6-10 and 7-10), the coefficients for planning districts 3 through 10 are generally different from each other. However, the hypothesis that the coefficient for planning district 11 is equal to that for planning districts 12 through 16 can be supported by the results of the likelihood ratio test. It is interesting to note that planning districts 11 through 16 are all recently developed suburbs in the eastern periphery of Metropolitan Toronto. These findings suggest that planning districts 1 and 2, and 11 through 16 constitute two groups that are similar internally but are distinctly different from each other in terms of their effect on trip-making propensities.

Accessibility

The accessibility coefficients are first examined for sign to find out whether they confirm intuitive expectation. It is expected that, all else being held equal, higher accessibility levels mean more trips. Thus, the expectation is for the coefficients of the accessibility measures to have a positive sign.

All the coefficients of the accessibility indices given by the AS model (Table 3.6, top entries) have negative signs for Metropolitan Toronto. An asymptotic t-test of the hypothesis that each of the coefficients of the accessibility measures in the Metropolitan Toronto is equal to zero is rejected at the 0.001 level.

Table 3.6 Estimated coefficients, standard errors and z-values of the accessibility indices

Index	Coefficient	Standard Error	z-value
Metro-wide			
A1	-0.000164	0.000017	-9.523
A2	-0.000278	0.000031	-8.987
A3	-0.000557	0.000075	-7.402
A4	-0.000030	0.000003	-9.381
A5	-0.000062	0.000006	-10.049
A6	-0.000175	0.000019	-9.141
A7	-0.000574	0.000079	-7.251
Core			
A1	-0.000123	0.000031	-4.093
A2	-0.000186	0.000048	-3.873
A3	-0.000308	0.000101	-3.063
A4	-0.000028	0.000008	-3.391
A5	-0.000058	0.000012	-4.679
A6	-0.000127	0.000028	-4.557
A7	-0.000338	0.000101	-3.341
Periphery			
A1	-0.000038	0.000029	-1.319*
A2	-0.000085	0.000053	-1.612*
A3	-0.000255	0.000126	-2.019
A4	-0.000004	0.000005	-0.736*
A5	-0.000009	0.000011	-0.874*
A6	-0.000049	0.000035	-1.423*
A7	-0.000280	0.000141	-1.981

$A1 = \sum_J d_J t_{ij}^{-1.5}$

$A2 = \sum_J d_J t_{ij}^{-2}$

$A3 = \sum_J d_J t_{ij}^{-3}$

$A4 = \sum_J d_J \exp(-0.14 t_{ij})$

$A5 = \sum_J d_J \exp(-0.25 t_{ij})$

$A6 = \sum_J d_J \exp(-0.5 t_{ij})$

$A7 = \sum_J d_J \exp(-t_{ij})$

* not significant at 0.1

The negative estimated coefficient of each of the accessibility indices suggests that an improvement in accessibility levels is paradoxically associated with a decrease in trip making propensities. The spatial pattern of accessibility in the Metropolitan Toronto inaicates that accessibility is higher in the central city, and lower toward the edges. The negative sign of the accessibility coefficients therefore means that there are more shopping trips toward the periphery than in the centre. It is important to emphasize that some empirical works that have used similar accessibility measures in regression models have reported this 'pathological effect' of the accessibility index. For instance, Ortuzar and Willumsen (1990) have indicated that the "estimated parameters of the accessibility variable have either been non-significant or with the wrong sign".

Given the counter-intuitive, negative sign of the estimated coefficients of the accessibility indices at the metro scale, further investigations into the accessibility measures were made. The effect of the accessibility indices at different geographic scales, and the contribution, if any, of accessibility to the predictive ability of the AS model were therefore investigated. One geographic scale used is the planning district level. Another scale is to divide the metropolitan area into core and periphery, and analyze the data at this level.

The data set for the metropolitan area was divided into core and periphery, and an AS model was estimated for each area. The core area consists of six planning districts (1, 2, 3, 4, 5, and 6), comprising 44.7 percent of the data. The remaining ten planning districts, with 55.3 percent of the data, make up the periphery. All the coefficients of the accessibility indices estimated on the core and periphery data in the AS model have a negative sign, but only two of the indices in the periphery are significant (Table 3.6).

With the negative estimated coefficient of all the accessibility measures at the metropolitan, core and periphery levels, it was important to determine if this is also the case at the planning district level. The AS model was therefore estimated for each planning district. The estimation results are found in Table 3.7. Six planning districts (1, 3, 10, 11, 13 and 14 in Figure 3.2) have the estimated coefficients of all the accessibility indices to be positive, but not all of them are significant. Both planning districts 3 and 10 have A1, A2, and A6 to be statistically significant. Planning district 3 has in addition A3 and A7 to be significant, while the z-values of the estimated coefficients of A4 and A5 indicate significance in planning district 10. There is only one accessibility index, A4, that is significant in planning district 13. Planning districts 4, 7 and 8 have the estimated coefficients of only A4, A5 and A3 respectively to be positive, but with very low z-values. The coefficient of A5 is also positive but not significant in planning district 7.

The contribution of accessibility to the predictive ability of the AS model was assessed by comparing the aggregate predicted probabilities given by the model, with and without the accessibility index as an explanatory variable, to the observed ones. Aggregate observed and predicted probabilities were calculated as a relative frequency:

$$A_j = \sum_{n=1}^{N} P_{nj} / N$$

where
A_j is the aggregate probability that households will generate j trips
P_{nj} is the probability that n makes j trips
N is the number of observations.

Table 3.7 Estimated coefficients of accessibility indices for each planning district (AS model)

Planning district	Accessibility Index						
	A1	A2	A3	A4	A5	A6	A7
1	0.0000326	0.0000408	0.0000714	0.0000249	0.0000221	0.0000241	0.0000663
	0.345	*0.351*	*0.383*	*0.38*	*0.314*	*0.264*	*0.322*
2	-0.0000112	-0.0001576	-0.0002300	-0.0002296	-0.0000367	-0.0000519	-0.0001062
	-1.085	*-0.971*	*-0.637*	*-1.17*	*-1.274*	*-1.191*	*-0.839*
3	0.0001609	0.0002763	0.0005311	0.0000239	0.0000368	0.0002010	0.0006177
	1.642	*1.945*	*2.148*	*0.546*	*0.886*	*1.837*	*2.155*
4	-0.0000234	-0.0000870	-0.0002703	0.0000215	-0.0000040	-0.0000496	-0.0002781
	-0.218	*-0.515*	*-0.784*	*0.739*	*-0.105*	*-0.529*	*-0.714*
5	-0.0004666	-0.0006879	-0.0010399	-0.0000555	-0.0001525	-0.0004182	-0.0011523
	-1.362	*-1.347*	*-1.101*	*-0.668*	*-1.308*	*-1.516*	*-1.139*
6	-0.0004531	-0.0007825	-0.0008117	-0.0000698	-0.0001321	-0.0004454	-0.0003525
	-2.958	*-2.580*	*-1.167*	*-2.995*	*-3.096*	*-2.635*	*-0.471*
7	-0.0000572	-0.0002390	-0.0015036	0.0000096	0.0000100	-0.0000651	-0.0009286
	-0.180	*-0.413*	*-0.920*	*0.167*	*0.086*	*-0.198*	*-0.703*
8	-0.0000259	-0.0000220	0.0000078	-0.0000146	-0.0000171	-0.0000151	-0.0000355
	-0.217	*-0.123*	*0.022*	*-0.460*	*-0.344*	*-0.138*	*-0.098*
9	-0.0001736	-0.0005045	-0.0022472	-0.0000160	-0.0000429	-0.0003161	-0.0024589
	-0.736	*-0.967*	*-1.407*	*-0.483*	*-0.579*	*-0.87*	*-1.276*
10	0.0003375	0.0004770	0.0002031	0.0000645	0.0001327	0.0004403	0.0005735
	2.777	*2.112*	*0.429*	*3.251*	*3.219*	*2.740*	*0.882*
11	0.0000749	0.0001709	0.0004783	0.0000070	0.0000145	0.0001004	0.0006232
	0.960	*1.239*	*1.607*	*0.492*	*0.515*	*0.989*	*1.688*
12	-0.0001086	-0.0001845	-0.0003855	-0.0000212	-0.0000279	-0.0000909	-0.0004420
	-0.796	*-0.932*	*-1.137*	*-0.577*	*-0.434*	*-0.536*	*-0.978*
13	0.0001401	0.0002179	0.0003058	0.0000300	0.0000587	0.0001434	0.0004202
	1.458	*1.256*	*0.720*	*1.679*	*1.607*	*1.294*	*0.975*
14	0.0000337	0.0000920	0.0003196	0.0000030	0.0000099	0.0000418	0.0003189
	0.132	*0.188*	*0.277*	*0.072*	*0.100*	*0.114*	*0.234*
15	-0.0003820	-0.0009720	-0.0044600	-0.0000448	-0.0001078	-0.0005261	-0.0043111
	-1.301	*-1.527*	*-1.889*	*-0.989*	*-1.133*	*-1.440*	*-1.872*
16	-0.0001694	-0.0003389	-0.0011395	-0.0000287	-0.0000543	-0.0001800	-0.0010637
	-1.901	*-1.934*	*-2.010*	*-1.626*	*-1.744*	*-1.755*	*-2.001*

123 significant at 0.1 level
figures in italics are the z-values

The assessment of the predictive ability of the model with and without an accessibility index was done for planning districts 10 (which has the coefficient of the accessibility indices A1, A2, A4, A5 and A6 to be positive and significant), and 16 (which was arbitrarily selected and has negative estimated coefficients for all the accessibility indices), and for Metropolitan Toronto. To ensure consistency in comparing the results, only the five accessibility indices which were found to be significant in planning district 10 were used in the analysis for Metropolitan Toronto and planning district 16. The results of the predictive test (Table 3.8) show that the predicted probabilities for making one or more trips given by the model with and without an accessibility index are virtually the same, and they all correspond to the observed probability very well for each of the three cases. (The effect of any one of the five accessibility indices used on the predictive ability of the model is the same, so only the results for one accessibility index are shown in Table 3.8). The major conclusion from this comparative analysis is that there are no differences in predicted trip-making behavior as a result of inclusion of the accessibility measure.

Issues arising from the negative coefficients of the accessibility measures

The negative sign of the estimated coefficients of the accessibility indices raises three important issues. One is the possible cause. Six factors may explain the negative sign of the indices. These are the level of aggregation at which the accessibility indices were calculated, focus on auto trips, changing lifestyles of households, possible correlation between the number of vehicles owned by a household and accessibility, restricting the study to Metropolitan Toronto, and the effect of household income.

Table 3.8 Effect of accessibility on the predictive ability of the AS model

Trips	Observed Probability	Predicted probability for making trips: with accessibility (A1)	Predicted probability for making trips: no accessibility
Metropolitan Toronto			
0	0.8251	0.8244	0.8245
1	0.1200	0.1204	0.1203
2	0.0469	0.0472	0.0472
3	0.0058	0.0058	0.0058
4	0.0018	0.0018	0.0018
5	0.0002	0.0002	0.0002
6	0.0001	0.0001	0.0001
7	0.0001	0.0001	0.0001
Planning district 10			
0	0.8414	0.8412	0.8410
1	0.1053	0.1055	0.1055
2	0.0456	0.0457	0.0457
3	0.0064	0.0064	0.0064
4	0.0013	0.0013	0.0013
Planning district 16			
0	0.8148	0.8151	0.8151
1	0.1286	0.1282	0.1283
2	0.0461	0.0461	0.0461
3	0.0083	0.0084	0.0084
4	0.0018	0.0018	0.0018
5	0.0004	0.0004	0.0004

note: columns may not add to 1 due to rounding error

The first possible cause for the negative sign is the aggregate level at which the indices were computed, which might have provided an inadequate basis for reproducing variation between household circumstances at the metro level, or in some of the planning districts, or in the core and the periphery. (Recall that the accessibility value for a traffic zone was assigned to all households in that zone.) This may, however, be refuted. According to Table 3.9 there is variability in each of the accessibility indices, but the amount of variability is not restricted to where the coefficient is positive and significant.

The second possible cause is the focus of the analysis on auto trips. There is the tendency for shop trips in the central city (which has a higher level of accessibility) to be made by other modes such as transit, bike or walk. Less than 0.05 percent of total trips were removed by focusing on auto trips. These non-auto trips are, however, non-uniformly located within the Metropolitan Toronto: they are more in the core area than in the periphery.

The third possible cause arises from Giuliano's (1995) observation that changing lifestyles have made accessibility a non-important factor in people's location choice. The author reports the results of a survey of 600 residents conducted in Orange County, California, to determine the most important factors affecting people's location choice decision. Accessibility was ranked sixth (with 4 percent of the total responses) out of the ten factors considered. Living far away from the metropolitan core, which scored 23 percent of the total responses, is the number one answer given by the respondents. The relatively well developed transportation system coupled with a comparatively very cheap price of private vehicle travel in most metropolitan areas in the western industrialised world may mean that accessibility is no longer a key factor in the travel decisions of households.

Table 3.9 Coefficient of variation for accessibility indices: planning districts, core, periphery and metro.

Planning District	Coefficient of variation						
	A1	A2	A3	A4	A5	A6	A7
1	15.27	25.53	48.74	4.47	9.18	21.24	43.88
2	16.35	25.06	41.81	9.24	18.12	35.51	47.79
3	12.51	20.81	46.44	8.72	13.04	22.21	48.73
4	10.53	[illegible]	32.39	6.64	12.58	23.34	34.57
5	4.49	7.99	19.33	2.97	5.71	12.05	22.12
6	9.50	12.35	22.99	10.58	15.80	18.76	25.48
7	10.76	16.41	28.05	10.19	15.11	25.65	39.68
8	10.86	19.78	47.96	6.77	12.47	28.07	57.46
9	11.12	13.44	18.43	14.14	18.27	16.20	16.04
10	13.53	17.44	30.18	15.21	19.12	19.46	24.64
11	19.57	29.41	55.82	17.68	26.45	37.37	57.88
12	14.17	24.80	56.15	8.85	14.10	24.64	50.27
13	13.43	18.74	31.15	12.80	16.60	22.74	34.30
14	11.84	17.56	35.81	12.43	16.09	22.48	39.98
15	13.78	20.28	34.74	15.84	26.49	39.71	46.15
16	17.85	23.30	33.11	18.13	25.03	32.16	37.82
Core	19.63	31.47	58.03	11.55	20.65	42.10	66.91
Periphery	19.45	28.13	50.97	18.76	25.62	35.87	52.26
Metro	24.65	36.09	62.27	21.14	30.70	47.37	68.98

coefficient of variation: standard deviation / mean * 100

The fourth possible cause of the negative coefficients for the accessibility measures is that the number of vehicles owned by a household and the accessibility measures are not truly independent. A simple correlation analysis revealed that the number of vehicles is negatively correlated with each of the seven accessibility indices. The magnitude of this negative relationship is very small, ranging from -0.1427 to -0.1094. This indicates that car ownership and accessibility can be treated as independent for the analysis.

The fifth possible cause is the relatively uniform density of land use in Metropolitan Toronto as compared to the Greater Toronto Area (GTA). Metropolitan Toronto has only 16 out of the 46 planning districts in the GTA. It is therefore possible that there could be more variability in the accessibility measures had the whole GTA been used in the analysis.

The final possible cause is the confounding effect of household income, which could not be used in the analysis. It is reasonable to expect households with higher incomes but lower accessibility levels to make more trips. One way to test for this possible cause would be to compute the correlation between average household income and accessibility. The problem, however, is that the data on accessibility and average household income are at different levels of aggregation. Accessibility data are available at the traffic zone level; average household income are available at the municipal level. However, car ownership may be correlated with income (Meyer and Miller, 1984). Hutchinson (1974, p.34) has suggested that some proxy for income, cars per household or occupation of the household head, may be used where income data are not available. The use of car ownership in the analysis might have picked up the income effect. Exclusion of income is therefore not expected to significantly account for the negative sign of the coefficients of the accessibility indices.

The second issue relates to the definition of home-based shopping trips in the data base. In the TTS data, home-based shopping trips are those single-leg trips to or from home for the purpose of shopping. This definition was, however, not used. Instead, a home-based shopping trip as used in this study is one-way movement from home to a retail establishment only. With the TTS definition, there were 13,953 trips made by households with 1, 2, 3, or 4 vehicles, and five or less members. There were 6,497 trips when the latter definition is adopted. This number constitutes about 46.6 percent of 13,953. This may suggest that excluding shopping trips that had their destination as home (or the origin as retail establishment) impiies that households made fewer trips despite the relatively high accessibility levels, and hence the negative signs of the estimated parameters of the accessibility indices. But a comparison of planning districts 10 and 16 suggests otherwise. Recall that the estimated parameters of all the accessibility measures in planning district 10 are positive, and five are significant at the 0.1 level. Planning district 16 has all the estimated coefficients of the accessibility measures to be negative, and not significant. The percentage of total home-based shopping trips as defined in this study to the total shopping trips based on the TTS definition is about the same (46 percent) for both planning districts. Clearly, excluding shopping trips that had their origin at a retail establishment could not significantly account for the negative estimated coefficient of the accessibility indices.

The adoption of single-leg trips from home to shop in this study was necessary for one reason: one objective of deriving an accessibility measure is to determine the accessibility of households *living* at some known reference 'points' to all possible destinations. It therefore does not make much sense to include shopping trips which have their origin as retail establishments.

The last issue arising from the negative sign of the accessibility coefficients relates to the suggestion that movement behavior cannot be explained simply by reference to the real, objective environment, but also by its psychological antecedents (Ajzen and Fishbein, 1980). If human subjectivity plays an important role in movement behavior, then it may be that the 'utilities' associated with accessibility are in part determined by the subjective attitudes, familiarity, and beliefs of households. Unfortunately, these factors are not among the set of explanatory variables used in the analyses. It is not possible to draw any conclusions about the possible effects of these subjective factors, especially when the results of empirical analysis of objective and subjective characteristics explaining overt behavior are mixed (Desbarat, 1983).

Relative strength of the planning district dummy variables and accessibility

The relative strength of the planning district dummy variables and the accessibility measures is also investigated. This is done by comparing the LS and AS models in terms of the statistical differences in fit. As a measure of fit, the pseudo R^2, adjusted for the number of estimated parameters is used. The measure is defined as

$$Å = 1 - ((L(\beta) - K) / L(c))$$

where
Å is the adjusted pseudo R^2
$L(\beta)$ is the log-likelihood of the model with all parameters
$L(c)$ is the log-likelihood of the model with only constants

K is the number of estimated parameters

Table 3.10 contains a measure of fit for the LS and AS models. Generally, it could be said that the better specified the model, the better the fit (higher adjusted pseudo R^2). If the fit to the estimation data constitutes the basis for logical preference of a particular model specification then the LS model with its higher adjusted pseudo R^2 would be preferred to all the AS submodels. It is, however, important to determine if the difference in fit between the LS model on one hand, and each of the seven AS submodels on the other hand, is statistically significant.

Since the AS models can be derived as a special case of the LS model (or vice versa) a likelihood ratio test is appropriate for the difference in fit between the models. The test is based on the difference between the log-likelihhod values of the two models which is asymptotically distributed as

$$\chi^2 = -2(L(\beta_{AS}) - L\beta(_{LS}))$$

with K_{LS} - K_{AS} degrees of freedom (df), and K is the number of estimated parameters. $L(\beta_{AS})$ and $L(\beta_{LS})$ are the log-likelihood values at estimated parameters for the AS and LS models respectively. The test statistics for each model pair are shown in Table 3.11. Since the critical χ^2 value at the 0.05 significance level is 23.685, it is concluded that the difference in fit is statistically significant.

The relationship between the accessibility measures and the planning district dummy

Table 10 Adjusted Pseudo R^2 for the LS and AS Models

Model	Adjusted Pseudo R^2
LS	0.0390
AS1	0.0301
AS2	0.0360
AS3	0.0352
AS4	0.0360
AS5	0.0365
AS6	0.0360
AS7	0.0351
SE	0.0338

note: AS1, AS2, etc. is the AS model with the accessibility index A1, A2, etc., and SE is the model with only socio-economic variables

Table 11 Test of difference in Adjusted Pseudo R^2 between the LS and AS, and SE and AS model pairs

Model pair	Test statistic
AS1 - LS	121.0
AS2 - LS	129.0
AS3 - LS	155.2
AS4 - LS	127.2
AS5 - LS	112.4
AS6 - LS	126.0
AS7 - LS	157.2
SE - AS1	94.2
SE - AS2	86.2
SE - AS3	60.0
SE - AS4	88.0
SE - AS5	102.8
SE - AS6	89.2
SE - AS7	58.0

variables is also explored. This is to help give a proper interpretation of the planning district dummy variables within the context of accessibility. The investigation is carried out by comparing the LS model (which has no accessibility index) and LAS model which has both the planning district dummy variables and an accessibility measure. All the accessibility indices in the LAS model are not statistically significant. The signs of the estimated accessibility indices from the LAS model are also not consistent with those obtained from the AS model. Two estimated indices (A3 and A7) have a positive sign instead of a negative sign. All but the planning district dummy variable specific to 2 are significant, according to the estimated results of the LAS model. This may suggest that the accessibility index does not have any impact at all on the effects of the planning district dummy variables.

A further investigation into the strength of accessibility was made by comparing each of the AS models to a model estimated on only the socio-economic variables in terms of statistical differences in fit. At a significance level of 0.05, the difference in fit is statistically significant (Table 3.11). This suggests that each of the AS submodels explains more than the model with only the socio-economic variables.

What is not clear from this comparative analysis is the role of the level of activities in each planning district on the accessibility measures. The effect of massive retail employment (d_j) on the accessibility indices is therefore investigated at a finer level of spatial disaggregation, a TARMS zone. Tests were conducted to determine if a TARMS zone is so large a retail concentration (d_j) that with any of the accessibility measures it will dominate the total with the result that all zones will have the same access. The average (350), the highest (3,962 in the planning district 1, downtown Toronto) and two other values (1,006 and 2,124) from the retail shopping employment data were inserted into the power and the exponential functions used to plot Figures 3.1a and b. Two parameter values, one for the power function (1.5) and another for the exponential function (0.25) were also used. The effect of d_j on the accessibility measure can be determine by relating $d_j f(t_{ij})$ to $\sum_j d_j f(t_{ij})$ (Figures 3.3a and b). Using Figure 3.3a as an example, the contribution of $d_j = 3962$ to the maximum value of accessibility index derived from the function $\sum_j d_j t_{ij}^{-1.5}$ (the maximum value of A1 is 9765) at travel time of about 7.5 minutes is only two percent (200/9765*100). The maximum contribution of $d_j = 3{,}962$ is only 14.34 percent of the maximum accessibility index at a travel time of 3.65 minutes. If massive retail employment is to overwhelm the accessibility index, the travel time for any x percentage (for $x > 0$) contribution of d_j should be the same. This is, however, not the case and so a high concentration of retail employment does not have any dominant influence on the accessibility measures.

3.7 CONCLUSIONS

The results of the study demonstrate no effect of accessibility on weekday, home-based shopping trip-making behavior in Metropolitan Toronto. From the Transportation Tomorrow Survey which was carried out in late 1986, information on households' travel patterns and socio-economic behavior, and network data were obtained. Additional data on retail shopping employment were provided by the Metropolitan Toronto Planning Department. Gravity measures of accessibility were calculated using travel time and retail shopping employment at the traffic zone level. All households within a traffic zone were assigned the accessibility value for the zone. A negative exponential and an inverse power function of

Figure 3.3a Influence of d_j on accessibility measure, $(t_{ij}^{-1.5})d_j$

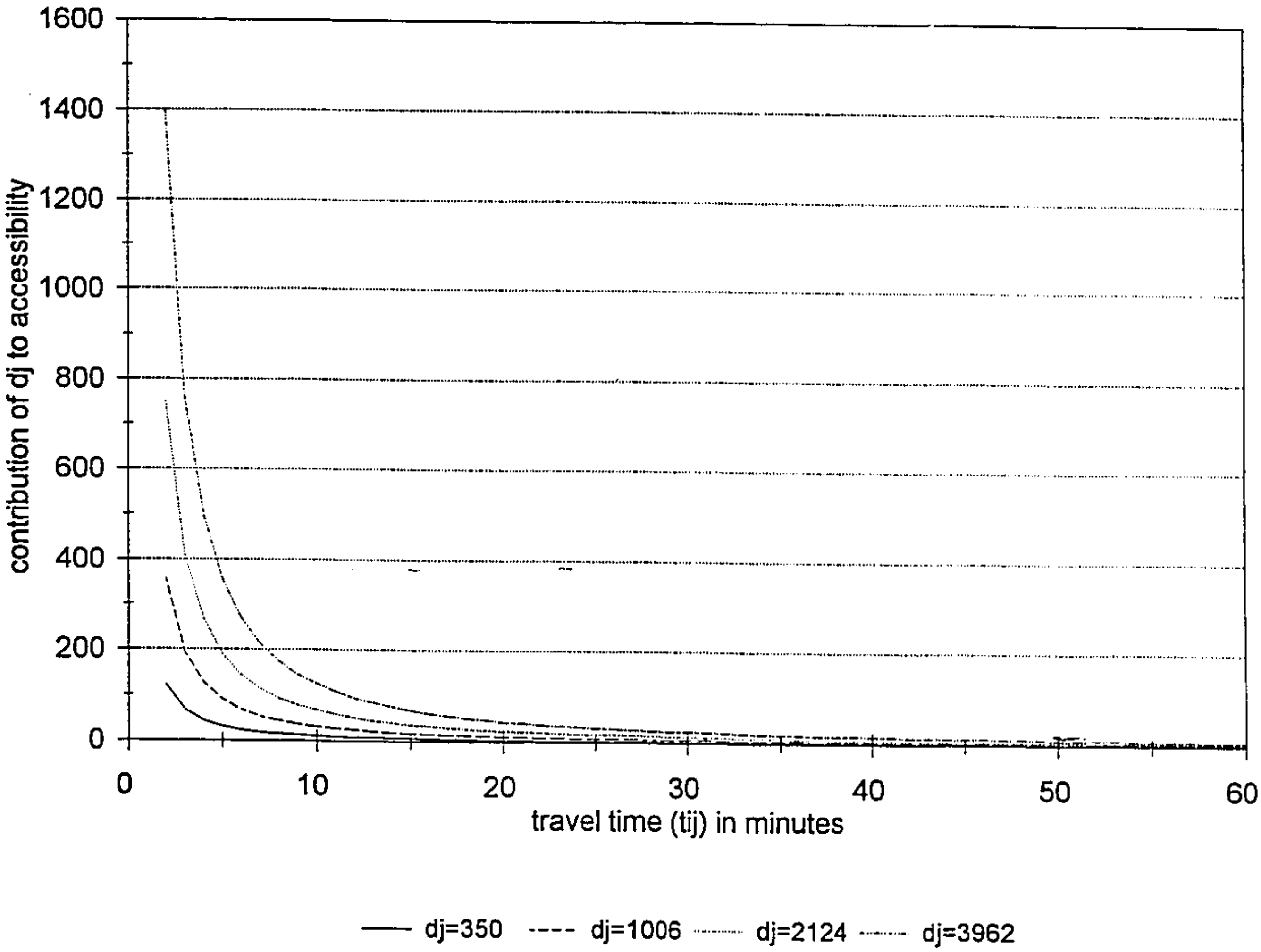
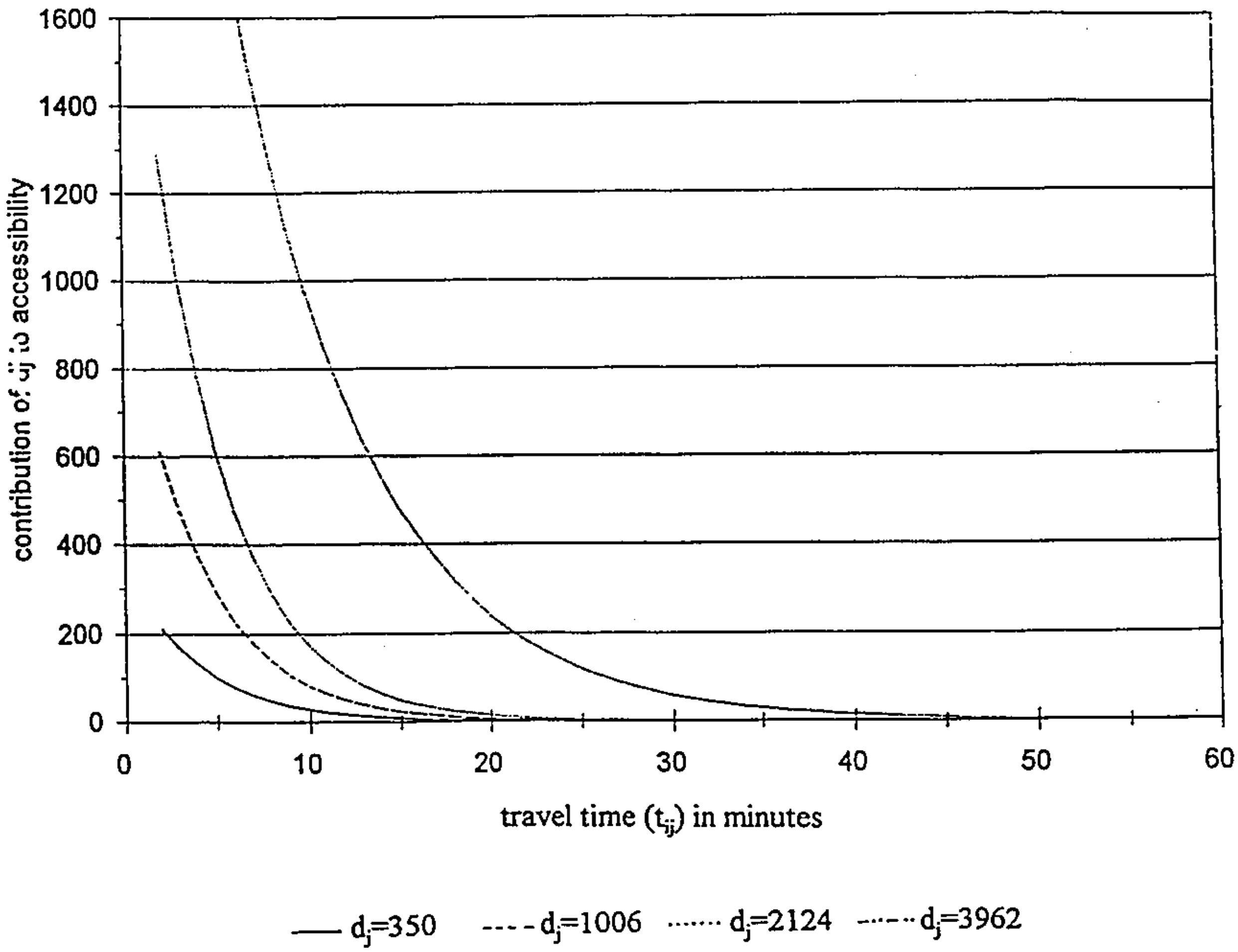


Figure 3.3b Influence of d_j on accessibility measure, $\exp(-0.25t_{ij})\ d_j$



travel impedance were used in the gravity measures of accessibility. A graphical approach was adopted to select seven different parameter values for the travel impedance function, three for the power function and the remaining four for the exponential function. These values represent different levels of perception of travel time as a deterrent to trip generation.

Analyses were performed for Metropolitan Toronto as a whole, for its core and periphery areas, and for each of the 16 planning districts in it using an ordered response model. Several models were estimated, one for each accessibility index, in addition to the household characteristics. The results of the analysis in terms of asymptotic *t*-statistics suggest that accessibility is not a significant input into households' travel decisions in the metropolitan area as a whole, neither the core nor the periphery. Six planning districts have positive estimated coefficients of all the accessibility measures, but not all of them are significant.

All the accessibility coefficients estimated on the data sets for Metropolitan Toronto, as well as the core and the periphery, and 10 planning districts have a negative sign. This implies that an increase in accessibility levels is paradoxically associated with a decrease in the probability of making trips. However, the magnitude of the negative effect appears to be quite small.

A shortcoming of the study is the calculation of the accessibility measures at the level of traffic zone instead of at a disaggregate, household level. Future research may be able to reduce its dependence on centroid-based network models and assignment procedures with increasing availability of geocoded trip data. This will go a long way to improve the network level-of-service measures such as travel time that will be generated and used in calculating the accessibility measures.

Finally, it was emphasized earlier in the chapter that travel is a derived demand, based on people's needs and desires to participate in activities at spatially-separated locations, what Jones (1977) called the activity linkage of travel. A shift from UTMS travel demand analysis to persons or households' activity patterns in general may lead to a better understanding of travel behavior. Nevertheless, the problems related to data collection in activity-based travel research are reasonably clear. Besides, satisfactory operational models of activity linkage in travel demand may be some time away although there have been some advances (Jones, Koppelman and Orfeuil, 1990). One way to proceed is to marginally push back some of the limitations of the current models by refining them.

CHAPTER 4

SPATIAL TRANSFERABILITY ANALYSIS[4]

4.1 INTRODUCTION

Transferability is an issue in two dimensions, space and time. Temporal transfer occurs when a model estimated in one time period in a specific geographic context is used in future forecasting in the same area. Spatial transfer, which is the focus in this chapter, involves applying a model estimated on data from one particular spatial entity to another geographic context. The importance of this type of transferability is well documented: to reduce substantially the need for costly full scale transportation surveys in different metropolitan areas or different areas in the same metropolitan area, and thus to allow for cost-effective analyses of transportation plans and policies.

Most transferability studies have focused on the time dimension and on transport mode choice: for instance the works of Parody (1977); Galbraith and Hensher (1982); Koppelman and Wilmot (1982); and recently Badoe (1994), who also has a comprehensive review of these works. Reports of studies on the transferability of trip generation models in general, and of spatial transfer in particular, are very rare. Doubleday (1977), Downes and Gyenes (1976) and a few others have looked at temporal transferability of category analysis and regression models of trip generation.

Perhaps the only investigation of spatial transferability is that by Rose and Koppelman (1984), who investigated the spatial transfer of a disaggregate, three-variable linear regression

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[4]This chapter has been submitted to *Transportation Research- A* with few changes.

model , both within and between urban regions. There are two problems associated with their study of spatial transferability. The first is the use of a regression model. The lack of built-in upper limits for trip rates as the values of the explanatory variables increase, and the possibility of predicting negative trips both mean that regression models are not wholly suitable for trip generation analyses.

The second probiem is the exclusion of variables dealing with cost of travel, accessibility, or locational factors that may affect trip generation. For instance, Rose and Koppelman (1984) used persons per household, vehicles available per household, and number of workers per household as the only explanatory variables in their study. Studies of the spatial transferability of better trip generation models are needed given the paucity of research work and the type of models and explanatory variables used.

There are two objectives of this chapter. The first objective is to investigate the performance of a directly transferred ordered response model (without updating the transferred coefficients). The second objective is to assess the effectiveness of a technique proposed by Koppelman, Kuah and Wilmot (1985) for revising the constant terms and scalars in an ordered response model by using sample data from the region to which it is to be applied. (They refer to this technique as "scaling parameter updating").

The rest of the chapter is organized as follows. First, the research approach is described. The model used, the data sources and the framework of analysis are described in this section. This is followed by estimating the model, and testing for parameter transferability. Then the measures for assessing transfer effectiveness are presented. Following this section is the empirical evaluation of transferability without parameter updating. This is followed by a brief discussion of a technique for updating the transferred coefficients, and an assessment of the effect of this technique on transfer effectiveness. The final section sets forth conclusions and implications of the study.

4.2 APPROACH

Three things are discussed in this section. These are the description of the model used in the analysis, the data sources, and the framework of analysis.

4.2.1 Description of the Model Used[5]

The model used in the analysis is similar in structure to the probit model developed by McKelvey and Zavoina (1975) for the analysis of Congressional voting on the 1965 Medicare Bill, by Sheffi (1979) in the analysis of trip generation behavior of elderly persons in Washington, D.C., and by Bhat and Koppelman (1993) for modelling household income and employment. The ordered response model is an extension of the better known binomial and multinomial logit models. The binomial logit model is used to predict the probability that a categorical variable will take on one of two possible values. In this case it does not matter whether the variable is measured on an ordinal or a nominal scale. The multinomial logit model predicts probabilities for three or more values that a categorical variable can take on. In this case, it is assumed that the variable is measured on a nominal scale. (A common application is the choice among three or more travel modes.) The ordered response model is appropriate when the categorical variable takes on three or more possible values which are

[5]The model presented here is the same as the one described in chapters 2 and 3

subject to some logical ordering such as the number of trips generated from a household.

The ordered response model is based on the definition of an abstract score for each household, which can be interpreted in this application as the utility derived by a household from making shopping trips:

$$U_n = V_n + \varepsilon_n \tag{4.1}$$

where U_n is the "total" utility that household n derives from making trips, V_n is a systematic or "observed" utility, and ε_n is random component. The V_n is defined as a linear function of attributes of the household:

$$V_n = \beta X_n \tag{4.2}$$

where β and X_n are respectively a vector of parameters and a vector of household attributes used as independent variables. (A more general specification would include attributes of the choice alternatives in X, however no such attributes are employed in our analysis.) The random component is the part of the utility that is unknown to the researcher. The ordered response model assumes "local" instead of "global" utility maximization. Local utility maximization implies a choice situation where each binary decision consists of whether to accept the current value or "take one more" (Ben-Akiva and Lerman, 1985). The decision maker stops when the first local optimum is reached. Global utility maximization occurs when all alternatives in the choice set are simultaneously considered. The ordered response model was chosen over the ordered generalized extreme value model of Small (1987), which maximizes global utility, because of its simple mathematical structure which makes it more convenient for applied analysis.

The model also defines a set of 'cut points' associated with each of the possible outcomes. For example, suppose a household can make 0,1,2,...,J trips, where J is a maximum defined through inspection of the data. Define a cut point λ_1 such that household n will make zero trips if U_n is less than λ_1, or in probabilistic terms

$$P_{n0} = \Pr(\beta X_n + \varepsilon_n \leq \lambda_1) \qquad (4.3a)$$

where P_{n0} is the probability that household n makes zero trips. The probability that the household makes one trip is now defined as the probability that U_n is greater than λ_1 but less than a second cut point λ_2:

$$P_{n1} = \Pr(\lambda_1 < \beta X_n + \varepsilon_n \leq \lambda_2) \qquad (4.3b)$$

or more generally

$$P_{nj} = \Pr(\lambda_j < \beta X_n + \varepsilon_n \leq \lambda_{j+1}) \qquad (4.3c)$$

for j=1,...,J-1 and

$$P_{nJ} = 1 - \Pr(\ \beta X_n + \varepsilon_n \leq \lambda_J\ ) \qquad (4.3d)$$

Since it is not possible to observe the values of the random components ε_n, the empirical model is derived by making an assumption about their distribution. The random components are assumed logistically distributed:

$$F(\ \varepsilon_n\ ) = 1/(1+\exp(-\ \mu\ \varepsilon_n\ )) \qquad (4.4)$$

where μ is a positive scale parameter which is unobservable, therefore it is assumed that μ=1. Given these assumptions, an explicit form for (4.3a-d) can be written:

$$P_{n0} \ = 1\ /\ (1 + \exp(\beta X_n\ -\ \lambda_1)) \qquad (4.5a)$$

$$P_{n1} \ = 1\ /\ (1 + \exp(\beta X_n\ -\ \lambda_2)) - 1\ /\ (1 + \exp(\beta X_n\ -\ \lambda_1)) \qquad (4.5b)$$

.

.

$$P_{nj} \ = 1\ /\ (1 + \exp(\beta X_n\ -\ \lambda_{j+1})) - 1\ /\ (1 + \exp(\beta X_n\ -\ \lambda_j)) \qquad (4.5c)$$

for j=2,3,...,J-1,

$$P_{nJ} \ = 1 - 1\ /\ (1 + \exp(\beta X_n\ -\ \lambda_J)) \qquad (4.5d)$$

Estimates of β and $\lambda_1 \ldots \lambda_J$ may be obtained using the maximum likelihood method based on a set of observations (households) making 0, 1,...,or J trips for which the attribute data in X_n are available.

The ordered response model was chosen over the standard regression model and the multinomial logit for the following reasons. As mentioned earlier, there is the possibility of predicting negative trips with the standard regression model. The second reason is that the model predicts the whole distribution of the response levels unlike the standard regression approach which will at best predict the mean of the dependent variable. Finally, as compared to multinomial logit, the ordered response model offers a more efficient way to exploit the ordinal nature of the dependent variable. One can of course exploit the ordering of information with multinomial logit models, but that will mean specifying all explanatory variables as alternative-specific, which is less appropriate.

4.2.2 Data Sources

Two sources for the data were used. The Toronto Metropolitan Planning Department provided information on retail shopping employment in the metropolitan area. The remaining data were obtained from the Transportation Tomorrow Survey (TTS) which was conducted in 1986. The TTS was a telephone interview survey of a random sample of about 1.5 million households living the Greater Toronto Area (GTA), which has three of the twenty-five census metropolitan areas (CMA) in Canada. One of the three CMAs in the GTA, Toronto Metropolitan Area, is the focus of the study.

A condition in model transferability analysis is consistency in the data collection method, variable definition, questionnaire wording and coding conventions across all data sets used in the application contexts. The common data sources for all samples used in the analysis ensures that this condition is met.

4.2.3 Framework of Analysis

The research is confined to weekday, home-based shopping trips made by households in Metropolitan Toronto, Canada, with one or more vehicles. (Home-based shopping trips refer to single-leg trips from home to a retail establishment.) The analysis proceeded by dividing the metropolitan area into a series of study units (or "regions"); and separate analyses were performed for different pairs of regions. For each pair, the first region is the estimation context (the context in which the model is estimated) and the other region is considered as the application context (the new context in which the estimated model is to be applied). The choice of which region to use for the estimation and application context was arbitrary.

As a first step, the metropolitan area was divided into core and periphery. The rationale for this division is to determine the extent of model transfer effectiveness from the core to the periphery. A typical urban area does not consist of only the core or periphery but aspects of the two. It was therefore deemed appropriate to perform the transferability analysis by dividing the metropolitan area into East and West, each half comprising a part of the core and a part of the periphery. The core- periphery, and East-West regions (Figure 4.1) form Group 1.

In practice, one may not have to do transferability analysis at the metropolitan scale, but rather it may be at a smaller geographic level. It was therefore considered useful to do

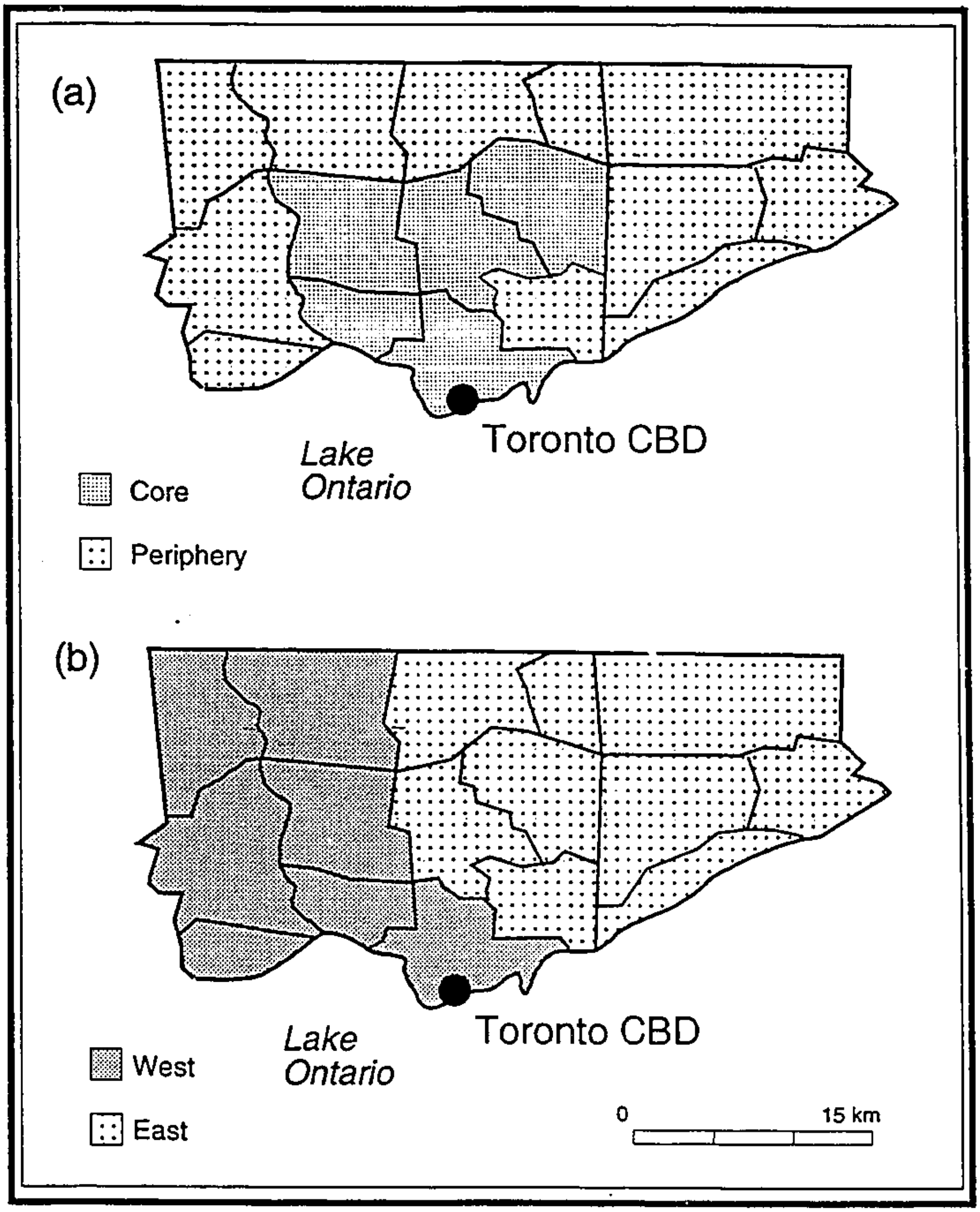

Figure 4.1 The study regions in Group 1.

the analysis for pairs of four of the six municipalities (also called regions for consistency) that form Metropolitan Toronto. These four regions (municipalities) constitute Group 2. Two of the municipalities, Toronto and East York form part of the core. The remaining two-- Scarborough and Etobicoke-- are in the periphery. Analyses were performed for the following pairs of municipalities: Toronto-Scarborough; Toronto-East York; and Scarborough-Etobicoke (Figure 4.2). For each pair, the first and the second city are respectively the estimation and application contexts.

A range of socio-economic variables that have been suggested by both theory and empirical studies of trip generation are included in the analysis. In addition, travel time and retail shopping employment were obtained in order to calculate a gravity-type accessibility index, another variable used. The dependent variable is the number of trips made by all members of a household in 24 hours. Three socio-demographic variables were specified as dummy variables: household size, number of children and vehicles. The remaining variables, which deal with employment, were entered in generic form: number of household members who are fully employed outside the home, who are working part-time outside the home, who are working at home and who are unemployed (Agyemang-Duah *et al*, 1995).

A positive correlation is expected between number of trips on the one hand, and household size and number of vehicles on the other hand. Household size should influence the demand for goods and/or services while the number of vehicles improves mobility. The presence of children in the family may have a dual influence on travel. On the one hand, it may lead to some restrictions on time available for shopping. Alternatively, it may be regarded as a scale factor leading to increased shopping trips. (The inclusion of household

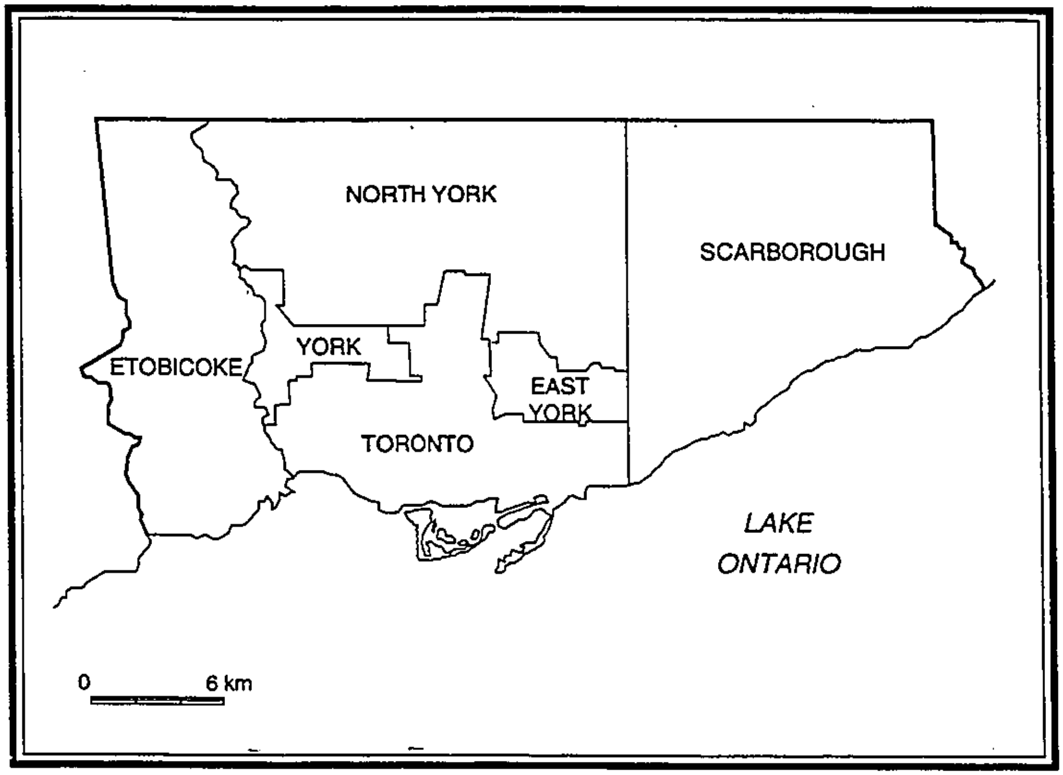

Figure 4.2 The study regions in Group 2

size controls for this scale effect to some extent, so that one might expect number of children to have a negative effect.) A negative influence of full time employment on the number of home-based trips made during the weekday is expected. There is no priori expectation regarding the effect of part-time employment and working at home. The lack of money might prevent the unemployed from making use of the time he/she has for shopping, so the effect of unemployment also cannot be determined a priori.

The accessibility index is a single factor, combining destination attractiveness measured by retail shopping employment, and travel time. This factor was calculated at the level of the traffic zone, of which there are 400. The form of the accessibility index used is

$$A_i = \sum_{j=1}^{400} d_j \exp(-\alpha t_{ij}) \qquad (4.6)$$

where
A_i is the accessibility index for origin zone i
d_j is the destination attractiveness
t_{ij} is the network travel time
α is a model parameter

The exponential function is used in the analysis. This is because, unlike the power function, it is bounded (Kanafani, 1983). That is, A_1 does not approach infinity when t_{ij} approaches zero or increases quickly as t_{ij} decreases.

Four different values of α were used in the exponential accessibility measures estimated in chapter 3, and all of them were not statistically significant. Therefore, the analysis does not provide any guidance with respect to which one to choose. A value of one was selected for α as a reasonable value.

The network travel time consists of inter- and intra-zonal travel time. The inter-zonal travel time was estimated by the TTS using a capacity restrained traffic assignment on their data. Intra-zonal travel time was estimated based on the following assumptions: each traffic zone is square in shape; all zones are identical in size; and the farthest point a person can travel within a traffic zone is half of the vertical/horizontal or diagonal distance. Since the average land area of a traffic zone is known (obtained by dividing the total land area of Metropolitan Toronto by the number of traffic zones), the length/width of a traffic zone is given by the square root of its average area. The maximum (diagonal) distance in a zone was determined according to Pythagoras Theorem. By the third assumption, intra-zonal travel distance is the average of the midpoints of the diagonal and the width/length of a zone. The travel distance was converted into travel time using the speed limit in the metropolitan area, which is 50 km/h.

A profile of all the study regions is given in Table 4.1. Important differences and similarities in the socio-economic indicators, shopping trip characteristics and accessibility are as follows. Overall, the mean accessibility index differs greatly from one region to another in both groups 1 and 2. The statistics on the number of trips, number of vehicles, and household members who are fully employed suggest great differences between the core and periphery samples. With the exception of accessibility, all the other variables appear to be similar in the east and west regions. Scarborough has the highest mean household size, while Toronto has the lowest. On the average, households in Etobicoke made more weekday, home-based shopping trips than any other region, yet it has the lowest mean accessibility

Table 4.1. Profile of the study regions

Group 1

Variable	Core		Periphery		East		West	
	mean	std.dev.	mean	std.dev.	mean	std.dev.	mean	std.dev.
Household size	2.59	1.28	2.93	1.26	2.78	1.27	2.77	1.30
Persons fully employed	1.33	0.86	1.43	0.91	1.36	0.88	1.41	0.91
Persons working part time	0.18	0.44	0.22	0.50	0.21	0.48	0.2	0.47
Persons working at home	0.04	0.22	0.03	0.20	0.04	0.21	0.03	0.20
Persons unemployed	1.04	1.11	1.24	1.12	1.17	1.13	1.13	1.11
Number of children	0.4	0.79	0.52	0.86	0.48	0.84	0.44	0.81
Number of vehicles	1.38	0.62	1.61	0.74	1.53	0.70	1.48	0.70
Accessibility index	460.66	308.22	282.41	147.59	314.15	146.22	429.09	334.42
Number of trips	0.18	0.51	0.28	0.64	0.25	0.59	0.22	0.57
Sample size	12094		14918		15716		11296	

Group 2

Variable	Toronto		Scarborough		East York		Etobicoke	
	mean	std.dev.	mean	std.dev.	mean	std.dev.	mean	std.dev.
Household size	2.42	1.26	3.03	1.27	2.68	1.25	2.8	1.22
Persons fully employed	1.28	0.84	1.49	0.90	1.37	0.87	1.37	0.93
Persons working part time	0.17	0.43	0.22	0.51	0.19	0.45	0.21	0.50
Persons working at home	0.04	0.22	0.03	0.19	0.04	0.22	0.04	0.50
Persons unemployed	0.93	1.07	1.29	1.14	1.08	1.12	1.18	1.09
Number of children	0.35	0.74	0.6	0.90	0.43	0.81	0.44	0.81
Number of vehicles	1.34	0.59	1.62	0.74	1.35	0.60	1.62	0.75
Accessibility index	580.73	381.71	266.03	133.34	310.5	79.38	230.82	111.87
Number of trips	0.15	0.45	0.28	0.63	0.21	0.54	0.32	0.68
Sample size	5920		6203		2309		4177	

value. The average number of vehicles in Scarborough and Etobicoke are the same, and it is similar to that in the periphery.

To determine the similarities and/or differences in the pairs of samples, a significance test of difference of means for the variables described earlier was performed. As a first step, an *F*-test was conducted to determine which of the two statistical tests (t-test or t-estimate) to use. The *F*-test, which tests for the equality of variance under the assumptions that the samples in each pair are independent, and that the distribution of the variables within them (samples) is a normal one, was based on the standard deviations (s) of the socio-demographic variables, the number of trips and the accessibility index. (*F* is computed simply as the larger standard deviation over the smaller one.) At the significance level of five percent, the hypothesis that the samples within each of the five pairs (core and periphery; East and West; Toronto and Scarborough; Toronto and East York; and Scarborough and Etobicoke) have equal variance was rejected. Therefore t-estimate was calculated as follows (King, 1969):

$$\text{t-estimate} = \bar{x}_1 - \bar{x}_2 / (s_1^2 / n_1 + s_2^2 / n_2)^{1/2} \qquad (4.7)$$

with degrees of freedom (df)

$$df = (s_1^2 / n_1 + s_2^2 / n_2)^2 / [(s_1^2 / n_1)^2 / n_1 - 1] + [(s_2^2 / n_2)^2 / n_2 - 1] \qquad (4.8)$$

The t-estimate tests the hypothesis that two regions have similar characteristics. Since the value of the t-estimate may be positive or negative, a two tailed test was performed. At the five percent significance level, the test indicated that with only a few exceptions, all pairs were significantly different (Table 4.2). The exceptions are household size in the core-periphery samples, and part-time employment in the Scarborough-Etobicoke samples. Two other variables, work-at-home and number of vehicles, are not statistically different on both the Toronto-East York and Scarborough-Etobicoke samples. Overall, the experimental populations in the samples are significantly different in many respects. This makes a stronger test for transferability.

4.3 ANALYSIS OF PARAMETER ESTIMATES

As a first step in the transferability of the model, the estimated coefficients in each pair of regions are compared. But before this comparison, the ordered response model estimates for each region are discussed. All estimations were performed using a Newton-Raphson Algorithm in STATA version 3.0. Besides presenting the coefficients and their standard errors, the STATA program also reports the asymptotic t-statistics and their corresponding asymptotic significance levels. The results of the ordered response model estimate for the two groups are presented in Tables 4.3a and b. The discussion of the estimated results is first done for Group 1 and then for Group 2. Note that the number of estimated cut points depends on the response levels (i.e. the number of trips in each sample). Hence some regions have more estimated cut points than others.

4.3.1 Estimated Results for Group 1 (Table 4.3a)

The household size dummy variables have their correct positive signs across all regions.

Table 4.2 Significance test of difference of means

Group 1

Variable	Core-Periphery t-estimate	Core-Periphery d.f.	East-West t-estimate	East-West d.f.
Household size	-21.861	25699	0.630	23992
Persons fully employed	-9.258	26386	-4.516	23840
Persons working part time	-6.988	26829	1.710	24629
Persons working at home	3.868	24727	3.969	25004
Persons unemployed	-14.666	25958	2.899	24585
Number of children	-11.930	26593	3.942	24839
Number of vehicles	-27.791	26981	5.791	24332
Accessibility index	58.403	16543	-34.252	14417
Number of trips	-14.291	27002	4.204	24813

Group 2

Variable	Toronto-Scarborough t-estimate	Toronto-Scarborough d.f.	Toronto-East York t-estimate	Toronto-East York d.f.	Etobicoke-Scarborough t-estimate	Etobicoke-Scarborough d.f.
Household size	-26.542	13611	-11.401	13615	-10.170	13581
Persons fully employed	-13.288	13531	-5.795	13588	-7.214	13608
Persons working part time	-5.845	13186	-2.502	13574	-1.090	13603
Persons working at home	2.673	13375	0.000	13614	1.443	9184
Persons unemployed	-17.935	13543	-7.541	13573	-5.431	13575
Number of children	-16.738	13064	-5.681	13480	-10.298	13437
Number of vehicles	-23.088	12898	-0.925	13605	0.000	13615
Accessibility index	60.035	8920	53.380	7957	-15.778	13163
Number of trips	-13.119	12192	-6.658	13130	3.356	13556

123 not significant at 0.05 for a two tailed test

Table 4.3a. Ordered Response Model estimates for Group 1

Variable	CORE Coeff.	CORE Std.error	CORE z-value	PERIPHERY Coeff.	PERIPHERY Std.error	PERIPHERY z-value	EAST Coeff.	EAST Std.error	EAST z-value	WEST Coeff.	WEST Std.error	WEST z-value
Cut point specific to												
trips = 1	2.15192	0.10613	20.276	1.80314	0.09834	18.336	1.94070	0.09910	19.583	1.92160	0.10880	17.662
trips = 2	3.55937	0.11318	31.449	3.10452	0.10190	30.466	3.30745	0.10315	32.064	3.20760	0.11407	28.120
trips = 3	5.70356	0.16647	34.262	5.03964	0.12579	40.064	5.35177	0.13280	40.299	5.13156	0.14917	34.401
trips = 4	7.30266	0.30677	23.805	6.25580	0.17534	35.678	6.65426	0.19747	33.698	6.44325	0.22671	28.421
trips = 5	-	-	-	7.80715	0.33086	23.597	8.57418	0.45780	18.729	8.05544	0.45978	17.520
trips = 6	-	-	-	8.72411	0.50938	17.127	9.08522	0.58559	15.515	9.66553	1.00570	9.611
trips = 7	-	-	-	9.41743	0.71377	13.194	10.18404	1.00478	10.136	-	-	-
Household size (HS) dummies specific to												
HS = 2	0.47156	0.08339	5.655	0.43856	0.07312	5.998	0.48318	0.07075	6.829	0.45028	0.08464	5.320
HS = 3	0.45574	0.11261	4.047	0.29111	0.08533	3.412	0.44335	0.08783	5.048	0.25795	0.10485	2.460
HS = 4	0.29885	0.14250	2.097	0.29898	0.09908	3.018	0.39854	0.10626	3.751	0.19934	0.12520	1.592
HS = 5	0.16327	0.18647	0.876	0.17493	0.12847	1.362	0.21567	0.13898	1.552	0.13458	0.16221	0.830
Household members												
fully employed	-0.27041	0.05261	-5.140	-0.23014	0.03858	-5.965	-0.24477	0.04095	-5.977	-0.22193	0.04710	-4.712
working part-time	0.02739	0.07185	0.381	0.16705	0.04922	3.394	0.15658	0.05213	3.004	0.10180	0.06378	1.596
working at home	0.35024	0.11250	3.113	0.09057	0.10248	0.884	0.26068	0.09395	2.775	0.10478	0.12779	0.820
unemployed	0.40674	0.04859	8.371	0.39387	0.03588	10.977	0.42643	0.03765	11.326	0.38127	0.04408	8.650
Children (CH) dummies specific to												
CH = 1	-0.37258	0.09262	-4.023	-0.47748	0.06867	-6.953	-0.50119	0.07111	-7.048	-0.34461	0.08734	-3.946
CH = 2	-0.56520	0.11962	-4.725	-0.62551	0.08253	-7.579	-0.67417	0.08568	-7.868	-0.49620	0.11080	-4.478
CH = 3	-0.89824	0.20492	-4.383	-0.79301	0.14422	-5.499	-0.83848	0.14864	-5.641	-0.87537	0.19404	-4.511
CH = 4	-0.94454	0.44409	-2.127	-0.80995	0.33758	-2.399	-1.07086	0.34484	-3.105	-0.61031	0.42306	-1.443
Vehicles (VH) dummies specific to												
VH = 2	0.32259	0.06234	5.175	0.23782	0.04759	4.997	0.24123	0.04826	4.999	0.37057	0.06007	6.169
VH = 3	0.40305	0.12577	3.205	0.42920	0.08118	5.287	0.49300	0.08657	5.695	0.43377	0.10782	4.023
VH = 4	0.97342	0.22595	4.308	0.71132	0.13374	5.319	0.69041	0.14923	4.626	1.05687	0.17857	5.919
Accessibility	-0.00033	0.00010	-3.300	-0.00028	0.00014	-2.000	-0.00044	0.00015	-2.933	-0.00058	0.00010	-5.800
Summary statistics												
Number of observations	12094			14918			15716			11296		
Chi-square	466.18			599.25			709.77			453.85		
Degree of freedom	16			16			16			16		
Prob > chi-square	0.0000			0.0000			0.0000			0.0000		
Log likelihood at constant	-6102.61			-10028			-9760.57			-6462.28		
Log likelihood at convergence	-5869.52			-9729.31			-9405.68			-6235.35		
Pseudo R^2	0.0382			0.0299			0.0364			0.0351		

0.123 = not significant at 0.05

(Note that these coefficients are relative to a household of size one, which by construction has a coefficient of zero). In general, the larger the household size, the smaller the estimated coefficient, which is very much unexpected. This implies that large household sizes have a negative effect on weekday, home-based shopping trips. This may be due to the fact that these households do their (large) shopping at the weekend, and not during the week. Examination of the estimated parameters of these dummy variables suggests that some of them are not significantly different from each other. A likelihood ratio test of the equality of these coefficients confirms this. For instance, the estimated coefficients for dummy variables specific to household size of two and three in the core are equal in the statistical sense. For model transfer purpose all such dummy variables were not constrained to be equal. The household size dummy variable specific to five across all divisions, and specific to four in the West are not statistically significant.

As expected, all the children dummy variables have negative estimated parameters, and a non-linear effect across all regions. All but the dummy variable specific to five children in the West region are significantly different from zero.

Full-time employment is negatively weighted across all areas, and it is significant. This is consistent with expectations given the time constraints this variable represents for weekday, home-based shopping trips. Part-time employment and the work-at-home variables are not significant in the core and the periphery respectively. Both variables are also not significant in the West. The effect of number of household members unemployed is positive and significant.

All the coefficients of the vehicle dummy variables are significant across all the four divisions. These coefficients increase with an increase in the number of vehicles, but they do so at a decreasing rate. This suggests that if the number of vehicles had entered the model as a generic variable, it would have given misleading results, even though these coefficients are monotonically increasing.

It is expected that accessibility will have a positive effect on weekday, home-based shopping trip frequency. For this reason, a one-tailed t-test was conducted. At a significance level of 0.05, the coefficient of the accessibility index is not significant. This coefficient has a negative sign, which is counter-intuitive. The negative sign suggests that improved accessibility leads to fewer rather than more trips.

4.3.2 Estimated Results for Group 2 (Table 4.3b)

As in Group 1, the expectation that increased household size will have a positive scale effect on shopping trip generation was not borne out as indicated by the generally decreasing size of the estimated coefficients across all municipalities. With the exception of East York, all the estimated household size dummy variables have the expected, positive signs. The negative sign of the dummy variable specific to household of five in East York is counter-intuitive, but not significant.

All the children dummy variables have the expected negative sign. The variables show a non-linear effect. Except for the dummy variable specific to four children in Toronto and in Etobicoke, they are all significant.

The fact that the estimated parameter for the dummy variable specific to three vehicles in Toronto is small and insignificant is contrary to a priori expectation. A likelihood ratio test

Table 3b. Ordered Response Model estimates for Group 2

Variable	TORONTO			EAST YORK			SCARBOROUGH			ETOBICOKE		
	Coeff.	Std.error	z-value	Coeff.	Std.error	z-value	Coeff.	Std.error	z-value	Coeff.	Std.error	z-value
Cut point specific to												
trips = 1	2.41824	0.15372	15.731	2.46276	0.32401	7.601	1.75787	0.16155	10.881	1.83452	0.17737	10.343
trips = 2	3.97330	0.16793	23.660	3.72583	0.33319	11.182	3.10713	0.16708	18.597	3.09015	0.18353	16.837
trips = 3	6.21910	0.27403	22.695	5.98665	0.42343	14.138	4.97365	0.20123	24.716	5.02975	0.22482	22.372
trips = 4	7.37675	0.43490	16.962	7.86818	0.77629	10.136	6.19268	0.27491	22.526	6.20101	0.30581	20.277
trips = 5	-	-	-	-	-	-	8.09415	0.59909	13.511	7.36833	0.48068	15.329
trips = 6	-	-	-	-	-	-	9.19337	1.01271	9.078	8.97945	1.01542	8.843
Household size (HS) dummies specific to												
HS = 2	0.54610	0.12307	4.437	0.53000	0.19872	2.667	0.49317	0.11876	4.153	0.38735	0.13281	2.917
HS = 3	0.47774	0.17418	2.743	0.60329	0.24314	2.481	0.36835	0.13503	2.728	0.23176	0.16414	1.412
HS = 4	0.49022	0.21599	2.270	0.02898	0.30197	0.096	0.57650	0.15492	3.721	0.18655	0.19884	0.938
HS = 5	0.04707	0.28715	0.164	-0.24908	0.41171	-0.605	0.41370	0.19940	2.075	0.04196	0.25786	0.163
Household members												
fully employed	-0.27320	0.08043	-3.397	-0.09018	0.11371	-0.793	-0.25429	0.06045	-4.207	-0.18540	0.07534	-2.461
working part-time	0.04636	0.10993	0.422	0.19432	0.15342	1.267	0.15377	0.07536	2.040	0.06963	0.09700	0.718
working at home	0.40890	0.16581	2.466	0.43771	0.25463	1.719	0.04621	0.16362	0.282	0.16503	0.18060	0.914
unemployed	0.43546	0.07403	5.882	0.59143	0.10433	5.669	0.34969	0.05674	6.163	0.43604	0.07154	6.095
Children (CH) dummies specific to												
CH = 1	-0.59484	0.15533	-3.830	-0.39610	0.18985	-2.086	-0.63692	0.10616	-6.000	-0.29680	0.12907	-2.300
CH = 2	-0.47291	0.18612	-2.541	-1.02239	0.27115	-3.771	-0.83412	0.12400	-6.727	-0.60340	0.16305	-3.701
CH = 3	-0.76036	0.32351	-2.350	-1.50811	0.51275	-2.941	-0.84350	0.21830	-3.864	-0.66177	0.27584	-2.399
CH = 4	-0.66872	0.65751	-1.017	-2.34251	1.13283	-2.068	-0.67552	0.48070	-1.405	-0.87504	0.74225	-1.179
Vehicles (VH) dummies specific to												
VH = 2	0.43689	0.09471	4.613	0.29398	0.14134	2.080	0.23024	0.07352	3.132	0.26082	0.08750	2.981
VH = 3	0.18064	0.22568	0.800	0.57132	0.29349	1.947	0.45436	0.12355	3.678	0.36419	0.15052	2.420
VH = 4	0.82711	0.39435	2.097	0.68783	0.51704	1.330	0.63764	0.20172	3.161	0.85769	0.24370	3.519
Accessibility	-0.00023	0.00012	-1.917	-0.00045	0.00075	-0.600	-0.00025	0.00024	-1.042	-0.00011	0.00034	-0.324
Summary statistics												
Number of observations	5920				2309		6203			4177		
Chi-square	243.95				112.88		247.91			176.30		
Degree of freedom	16				16		16			16		
Prob > chi-square	0.0000				0.0000		0.0000			0.0000		
Log likelihood at constant	-2633.85				-1253.06		-4167.69			-2986.94		
Log likelihood at convergence	-2511.87				-1196.62		-4043.73			-2898.79		
Pseudo R^2	0.0463				0.045		0.0297			0.0295		

123 not significant at 0.05

indicates that this variable could be forced to be equal to the parameters for the dummy variable specific to two or four vehicles. But it is retained for the purpose of model transferability as indicated earlier. In East York, the vehicle dummy variable specific to four is also not significant. As in Group 1, the accessibility index (which is still negatively weighted) is not statistically significant in all regions.

4.3.3 Comparison of Pairs of Estimated Coefficients for Model Transfer

An asymptotic t-test was performed to test the hypothesis that the corresponding model parameter estimates in the estimation and application contexts are equal. The test was based on the estimated coefficients and their variances. The test statistic used is (Ben-Akiva and Lerman, 1985)

$$t = \hat{\alpha}_{ki} - \hat{\alpha}_{kj} / [\text{variance}(\hat{\alpha}_{ki}) + \text{variance}(\hat{\alpha}_{kj})]^{1/2} \qquad (4.9)$$

where $\hat{\alpha}_{ki}$ is the estimated coefficient of variable k in context i.

A two tailed t-test at the significance level of 0.05 with a critical value of $\pm$1.960 was used. There was greater than normal concern for making a Type I error (rejecting a hypothesis when it should be accepted), hence the choice of a significance level of 0.05.

The test results, in Table 4.4, suggest that in almost all cases the coefficients in the two contexts are statistically equal. This is accepting the null hypothesis. The implication is that without any updating of any coefficient, the transfer model should perform well in the application context. This is tested in section 4.5.

Table 4.4 Comparison of pairs of estimated coefficients

	t-value				
	Group 1		Group 2		
Variables	Core-Pery	East-West	Tor-Sca	Tor-EY	Sca-Eto
Household size (HS) dummies specific to					
HS = 2	0.298	0.298	0.309	0.069	0.594
HS = 3	1.165	1.355	0.496	-0.420	0.643
HS = 4	-0.001	1.213	-0.325	1.242	1.547
HS = 5	-0.051	0.380	-1.049	0.590	1.140
Household members					
fully employed	-0.617	-0.366	-0.188	-1.314	-0.713
working part-time	-1.604	0.665	-0.806	-0.784	0.685
working at home	1.706	0.983	1.557	-0.095	-0.488
unemployed	0.213	0.779	0.920	-1.219	-0.946
Children (CH) dummies specific to					
CH = 1	0.910	-1.390	0.224	-0.810	-2.036
CH = 2	0.415	-1.271	1.615	1.671	-1.126
CH = 3	-0.420	0.151	0.213	1.233	-0.517
CH = 4	-0.241	-0.844	0.008	1.278	0.226
Vehicles (VH) dummies specific to					
VH = 2	1.080	-1.678	1.723	0.840	-0.267
VH = 3	-0.175	0.428	-1.064	-1.055	0.463
VH = 4	0.998	-1.575	0.428	0.214	-0.696
Accessibility	-0.289	0.777	0.075	0.288	-0.342

Pery = periphery Tor = Toronto Sca = Scarborough EY = East York Eto = Etobicoke

123 significant at 0.05 for a two-tailed test

According to the test of difference of means (Table 4.2), the values of the variables in each pair of regions are different. However, the magnitude of the impact of these variables are not different, as shown by the asymptotic t-test. The equality of most of the pairs of the estimated coefficients is an indication of how robust the ordered response model is.

4.4 MEASURES FOR ASSESSING TRANSFER EFFECTIVENESS

Four measures are defined to evaluate the effectiveness of the transferred models, with and without updating the transferred coefficients. The measures are transferred pseudo R^2 (TPR), weighted root mean square error (WRMSE), root of sum of residual squared (RSRS) and aggregate prediction statistic (APS). WRMSE and RSRS are measures of aggregate prediction errors, and TPR and APS are statistical measures of transferability. The definitions of these measures draw extensively on the work of Koppelman and Wilmot (1982). It is, however, important to note that the WRMSE and APS as defined here are based on aggregate observed and predicted probabilities instead of the number of persons or households observed and predicted to choose a particular alternative as used by these two authors. The transfer pseudo R^2 was not used by them, but its definition is based on ideas from the authors' definition of a goodness-of-fit measure for transferability. Aggregate observed and predicted probabilities were calculated as a relative frequency:

$$A_{rj} = \sum_{n=1}^{N} P_{nj} / N_r \qquad (4.10)$$

where

A_{rj} is the aggregate probability that households in region r generate j trips
N is the number of observations in a region.

The four measures are defined as follows.

Transfer Pseudo R^2 (TPR)

The transfer pseudo R^2 is used as a measure of goodness-of-fit of a transferred model. Pseudo R^2 is defined as $1 - L(\beta) / L(c)$ which is the log likelihood on a scale where c corresponds to a 'constant-only' model and β corresponds to model estimated with all the parameters. (The pseudo R^2 is used to discriminate different model specifications estimated on the same data set.) As a measure of fit in model transferability, the transfer pseudo R^2 describes the degree to which the log likelihood of the transferred model, $L_j(\beta_t)$, exceeds that of a model developed and estimated on the same data in the application context (local model), $L_j(\beta_a)$, relative to the improvement in the log likelihood given by a perfect model, also developed and estimated on the same data in the application context, L_{j*}:

$$TPR = [L_j(\beta_t) - L_j(\beta_a)] / [L_{j*} - L_j(\beta_a)] \qquad (4.11a)$$

For a perfect model, the likelihood function at estimated parameters would be one, since the probability of observing the choices that were actually made is one. The log of one is zero and so is the value of L_{j*}. Equation 4.11a is therefore reduced to

$$TPR = 1 - [L_j(\beta_t) / L_j(\beta_a)] \qquad (4.11b)$$

The transfer pseudo R^2 has an upper bound value equivalent to the pseudo R^2 given by the model developed and estimated in the application context (local model) and no lower bound (Koppelman and Wilmot, 1982). Negative values imply that the performance of the local model is better than the transferred model. It is not a simple matter to calculate transfer pseudo R^2 for a directly transferred model since this model is not re-estimated in the application context. This measure was therefore not calculated for the directly transferred model.

Weighted Root Mean Square Error (WRMSE)

This is a measure of the aggregate predictive accuracy of the transferred model. The measure is based on the average relative error in the aggregate predicted probabilities weighted by the predicted probabilities:

$$WRMSE = [\sum_k PP_k * RE_k^2]^{1/2} \qquad (4.12)$$

where
RE_k is the relative error in prediction for alternative k defined as $(PP_k - OP_k) / PP_k$
PP_k and OP_k are respectively the predicted and observed probabilities.

The squared relative error term in the equation (RE_k^2) is a way to penalize large prediction errors more than small ones. A weakness in the measure is the division by the predicted probability in calculating the relative error, RE_k. Where the predicted probability is zero, WRMSE cannot be calculated.

Root of Sum of Residual Squared (RSRS)

This is another measure of aggregate prediction error defined as

$$RSRS = [\sum_k (PP_k - OP_k)^2]^{1/2} \quad (4.13)$$

where PP_k and OP_k are defined as before.

By avoiding any division by the predicted probability, no error can occur in the calculation.

Aggregate Prediction Statistic (APS)

An alternative method to assess the performance of the transferred model is aggregate prediction statistic. Unlike the other measures, this is a statistical test measure distributed as chi-square (χ^2),

$$\chi^2 = \sum_k [(PP_k - OP_k)^2 / PP_k] \quad (4.14)$$

with degrees of freedom = number of alternatives - 1. This statistical measure is used to test the hypothesis that the observed choice probabilities in the application context are given by the transferred model. Like WRMSE, when the predicted probability is zero, APS cannot be computed.

4.5 EVALUATION OF TRANSFERABILITY WITHOUT PARAMETER UPDATING

This section reports the results of evaluating the transfer effectiveness of the ordered response model without any parameter updating. Such a model is called a directly transferred model.

It is important to emphasize that model transfer effectiveness implies the extent to which the transferred model provides information about travel behavior in the application context. The performance of the transfer model in a predictive mode is used as a measure of transfer effectiveness.

The directly transferred model was estimated on the data set in the estimation context, and, without any updating of the estimated parameters, it was used to predict the aggregate trip-making probabilities by households using the full data set in the application context. Three measures of transfer effectiveness (weighted root mean square error, root of sum of residual squared and aggregate prediction statistic) are used to evaluate the performance of the directly transferred model (Table 4.5).

The computed weighted root mean square error varies from 0.0412 to 0.2029. This measure indicates that the directly transferred model from East to West performs best, followed closely by the model transferred from Scarborough to Etobicoke. By this same measure, the worst directly transferred model is the one from Toronto to Scarborough. In general, the model directly transferred from the inner urban area (for example, Toronto) to the urban fringes (for instance, Scarborough) performs worse than those models estimated and applied in contexts with similar characteristics (for example, from East to West, from Scarborough to Etobicoke).

When the root of sum of residual squared measure is used, the model directly transferred from Scarborough to Etobicoke has the lowest prediction error, 0.0097, followed by the model transferred from East to West, with 0.0181 in prediction error. The worst performed directly transferred model is, once again, the one from Toronto to Scarborough.

Table 4.5 Performance of the directly transferred model in prediction mode.

Predicted probability for making trips in the Periphery using model estimated on Core data

Trips	Observed Probability	Predicted probability for making trips
0	0.7965	0.8404
1	0.1362	0.1136
2	0.0568	0.0404
3	0.0074	0.0045
4	0.0031	0.0012
WRMSE		0.1354
RSRS		0.0521
APS		0.0183

Predicted probability for making trips in the West using model estimated on East data

Trips	Observed Probability	Predicted probability for making trips
0	0.8387	0.8254
1	0.1091	0.1212
2	0.0441	0.0461
3	0.0059	0.0054
4	0.0018	0.0017
5	0.0005	0.0003
WRMSE		0.0412
RSRS		0.0181
APS		0.0017

Predicted probability for making trips in Scarborough using model estimated on Toronto data

Trips	Observed Probability	Predicted probability for making trips
0	0.7954	0.8560
1	0.1398	0.1083
2	0.0540	0.0318
3	0.0076	0.0027
4	0.0032	0.0012
WRMSE		0.2029
RSRS		0.0720
APS		0.0412

Table 4.5 (cont'd) Performance of the directly transferred model in prediction mode

Predicted probability for making trips in East York using model estimated on Toronto data

Trips	Observed Probability	Predicted probability for making trips
0	0.8480	0.8684
1	0.1018	0.0993
2	0.0446	0.0288
3	0.0048	0.0024
4	0.0009	0.0011
WRMSE		0.1079
RSRS		0.0260
APS		0.0012

Predicted probability for making trips in Etobicoke using model estimated on Scarborough data

Trips	Observed Probability	Predicted probability for making trips
0	0.7793	0.7847
1	0.1434	0.1461
2	0.0651	0.0576
3	0.0084	0.0081
4	0.0026	0.0029
5	0.0012	0.0005
WRMSE		0.0457
RSRS		0.0097
APS		0.0021

WRMSE = wieghted root mean square error
RSRS = root of sum of residual squared
APS = aggregate prediction statistic
note: observed and predicted probabilities may not add to 1 due to rounding error

The hypothesis that the observed aggregate probabilities in the application context are given by the directly transferred model cannot be rejected at a significance level of 0.05 in all the cases considered, according to the aggregate prediction statistic. Badoe (1994) and Koppelman and Wilmot (1982) have, however, obtained different results using this statistic.

Generally, the actual predicted probabilities for making one or more trips given by the directly transferred model correspond very well to the observed probabilities. The performance of the model in terms of under- or over-prediction varies from one context to another. The directly transferred model estimated on the core data set under-predicted in the periphery the observed probabilities for making one or more trips. Similar observations were made for Toronto-Scarborough and Toronto-East York pairs. For East-West and Scarborough-Etobicoke pairs, the observed probabilities were over-predicted by the directly transferred model.

The good predictive ability of the directly transferred model across different spatial contexts has a very important implication for the use of cross-sectional models. These models are criticised for not being able to account for habit or time-lag effects, since such models are only a snapshot of a particular historical event. According to the critics, such models do not, and cannot guarantee good response properties in another geographic setting, and/or for a future situation. For instance, Ortuzar and Willumsen (1990) have indicated that it is only when information is available on response over time that "real" progress in understanding and assessing the effectiveness of forecasting models can be made. The results reported here suggest the contrary. The generally very good performance of the transferred (ordered response) model without even accounting for contextual factors is indicative of "real" progress without the use of time-series data in travel demand analysis.

4.6 SCALING UPDATING OF THE TRANSFERRED COEFFICIENTS

Due to errors from different sources, no model is perfectly specified and hence transferable. It is expected that there will be differences in the parameter values of models of the two contexts in question. The difference in model parameter values in the two contexts is referred to as transfer bias. There are two possible causes of this transfer bias. One cause is the omission of potentially important variables. The other cause is changes in the parameter values of the random utility probability distribution assumed in the model. In order to account for this transfer bias, some updating of the estimated coefficients to be transferred is necessary. Updating the transferred coefficients is carried out by multiplying these coefficients by their corresponding variables in the application context and summing them for each observation.

It is also expected that the cut points are context-specific. The cut points account for the effect of factors influencing trip generation decisions but not explicitly included in the model specification. It is therefore important to re-estimate the cut points based on the information in the application context. Studies by Koppelman and Wilmot (1983), Train (1978) and Atherton and Ben-Akiva (1976) have confirmed the importance of adjusting alternative specific-constants (or the cut points) to improve the transferability of disaggregate choice models.

The variables in the data set can be put into two subgroups on the basis of their sensitivity to transportation policy instruments. The subgroups are socio-economic characteristics on which policy has little effect, and the accessibility factor which is jointly influenced by the network characteristics and the distribution of retail employment, and can therefore be subjected to policy manipulations. Given their different characteristics from a transportation policy viewpoint, it is expected that the importance of accessibility relative to the socio-economic variables will be different. The two sets of variables are therefore separated instead of combining them as done in most transferability studies.

Two partial utility variables, W^2 and M^2, (respectively for the socio-economic characteristics and the accessibility index) were created as follows:

$$W^2 = \sum_{i=1}^{I} \underline{\beta}_i^1 X_i^2 \quad \text{and,}$$

$$M^2 = \sum \underline{\delta}^1 A^2$$

where
1 and 2 are accordingly the estimation and application contexts
$\underline{\beta}_i$ is estimated coefficient for socio-economic variable i
X_i is the socio-economic variable i
$\underline{\delta}$ is the estimated accessibility coefficient
A is the accessibility value

The systematic component of the utility function in the application context is given as

$$V^2 = \phi W^2 + \tau M^2 \tag{4.15}$$

where ϕ and τ are constants or 'scalars' to be estimated. It is assumed that the scalar has a value of 1 if the underlying structure of behavior is the same across contexts. The scalars adjust the utility function in the application context. The approach to estimating the scalars and the cut points is referred to as transfer scaling (Koppelman, Kuah and Wilmot, 1985). It is important to note that the authors did not use two scalars in their analysis.

4.7 ASSESSMENT OF THE SCALING UPDATING TECHNIQUE

The essence of model transferability is to use limited information to assist in policy decisions. The estimated coefficients from the estimation contexts were therefore updated with information on a sample of households from the application contexts. The regions in Group 1 are at the metropolitan scale, so a sample size of 1500 was used. Those in Group 2 are at the municipal level, so a sample of only 500 was used. In practice, the amount of new information that will be needed to update the parameters is not likely to be the same for the two groups. The sample was selected on the assumption that the order of observations in the main sampling frame (i.e. the whole data set in the application context) is random. The sample sizes of 1500 from the periphery and the West regions in Group 1 constitute respectively 10 and 13 percent of the data set from these regions. A sample size of 500 from regions in Group 2 is about 8, 12 and 22 percent of the Scarborough, Etobicoke and East York data sets respectively.

The ordered response model was estimated using the utility function in equation 4.15. Table 4.6 gives the parameter estimates for the cut points specific to the application contexts and the two scalars. Since the estimated cut points depend on the response level in the data set, there are fewer of them in Table 4.6 than in Tables 4.3a and b. The estimated coefficients of the missing cut points in Table 4.6 are assumed to be zero. In general, the cut points in

Tabel 4.6 Parameter Estimates from the updated ordered response model

(a) Group 1

Variable	Periphery (Core) coeff.	Periphery (Core) z-value	West (East) coeff.	West (East) z-value
Cut point specific to				
trips=1	1.77378	8.915	2.72136	12.340
trips=2	3.26159	14.628	4.53576	15.823
trips=3	5.01940	15.255	6.68187	10.898
trips=4	7.66660	7.531	7.08935	9.624
Socio-economic scale	0.92160	7.084	1.05036	6.212
Accessibility scale	1.72403	0.868	-0.07957	-0.196
Summary statistics				
Number of observations	1500		1500	
Chi-square	50.98		37.3	
Degree of freedom	2		2	
Prob > chi-square	0.0000		0.0000	
Log likelihood at constant	-930		-537	
Log likelohood at convergence	-905		-518	
Pseudo R^2	0.027		0.035	

(b) Group 2

Variable	East York (Toronto) coeff.	East York (Toronto) z-value	Scarborough (Toronto) coeff.	Scarborough (Toronto) z-value	Etobicoke (Scarborough) coeff.	Etobicoke (Scarborough) z-value
Cut point specific to						
trips=1	1.64631	2.946	2.01345	5.508	1.73752	5.135
trips=2	3.18301	5.368	3.58378	8.862	3.01660	8.100
trips=3	-	-	5.36386	9.361	5.77519	7.418
Socio-economic scale	0.96335	4.462	0.72918	4.028	1.09745	4.737
Accessibility scale	9.99257	1.318	-3.01704	-0.760	3.27947	0.571
Summary statistics						
Number of observations	500		500		500	
Chi-square	22.56		17.16		22.70	
Degree of freedom	2		2		2	
Prob > chi-square	0.0000		0.0000		0.0000	
Log likelihood at constant	-244		-339		-294	
Log likelohood at convergen	-233		-331		-282	
Pseudo R^2	0.046		0.025		0.041	

123 not significant at 0.05 level

note: regions in brackets are the estimation contexts

Table 4.6 do not correspond with the original cut points in Tables 4.3a and b for the application context. The exceptions are the cut points specific to one and three trips in the periphery, and two trips in Etobicoke, which are very close. This suggests that the factors that are not explicitly included in the model specification but affect trip-making decisions are specific to each geographic entity.

Three regions-- periphery in Group 1, and East York and Etobicoke in Group 2-- have the accessibility scale to be positive but the original coefficient of the accessibility index from the estimation context is negative. The positive accessibility scale suggests that the new coefficient is still negative. It is the negative scalars that change the sign of the accessibility coefficient to positive. All the accessibility scalars also have relatively large standard errors, and hence their low z-values.

It was stated earlier that the value of the scalar is assumed to be 1 if the underlying structure of behavior is invariant over space or time. It is therefore necessary to determine if the scalars are significantly different from 1 in the application context. Statistical significance test cannot be used since such a test is always with respect to the difference from zero. It is probably impossible to estimate the statistical difference from 1 because the sample distribution under that assumption is not known. Asymptotic confidence intervals that contain the true value of the scalars at the 95 percent confidence level were therefore used. The confidence intervals were calculated as follows (Ben-Akiva and Lerman, 1985):

$$\hat{\omega}_k - z_{\alpha/2} * se(\hat{\omega}_k) \leq \omega_k \leq \hat{\omega}_k + z_{\alpha/2} * se(\hat{\omega}_k)$$

where
$\hat{\omega}_k$ is the estimated scalar k
$z_{\alpha/2}$ is the z value at the 95 percent degree of confidence
ω_k is the 'true' value of the scalar k
se is the standard error

The confidence intervals are reported in Table 4.7. The interval estimates for each accessibility scalar in four application contexts (periphery, Scarborough, East York and Etobicoke) includes 1. It can therefore be stated that the accessibility scale parameters in the these four estimation contexts are not significantly different from those in the application contexts. In the West, however, the confidence limits for the accessibility scalar are -0.8768 and 0.7177, which are less than unity. This suggests that households in the West and East (the estimation context) differ in the level of importance they attached to accessibility in trip generation decisions. The confidence interval for the socio-economic scalar in all application contexts also includes 1. In other words, it can be assumed that the underlying socio-economic parameters may be invariant over space.

Table 4.8 (columns 3, 4 and 5) contains the results which demonstrate the predictive performance of the updated model under three arbitrarily selected sample sizes (500, 1000 and 1500). Caution should be taken in drawing any conclusions on how sample size affects the predictive ability of the transferred model since this depends very much on the representativeness and not necessarily the size of the sample. According to the law of large numbers, it is, however, expected that the representativeness of a sample will correlate well with the size of the sample.

Examining the values of the weighted root mean square error and the root of sum of

Table 4.7 Confidence interval of the scalars

Scalar	Confidence interval min	Confidence interval max
Periphery		
Socio-economic	0.6666	1.1766
Accessibility	-2.0794	5.5274
West		
Socio-economic	0.7189	1.3818
Accessibility	-0.8768	0.7177
Scarborough		
Socio-economic	0.3744	1.0840
Accessibility	-10.8017	4.7676
East York		
Socio-economic	0.5401	1.3864
Accessibility	-4.8697	24.8550
Etobicoke		
Socio-economic	0.6434	1.5515
Accessibility	-7.9817	14.5406

Table 4.8 Predictive ability of the transferred scaled model

Predicted probability for making trips in the Periphery using model estimated on Core data

Trips	Observed Probability	Predicted probability for making trips: Transferred Scaled Model n = 500	n = 1000	n = 1500	n = 14918*	Directly Transferred Model n = 14918*
0	0.7965	0.8360	0.8151	0.8123	0.7957	0.8404
1	0.1362	0.1380	0.1419	0.1365	0.1366	0.1136
2	0.0568	0.0240	0.0319	0.0420	0.0571	0.0404
3	0.0074	0.0020	0.0110	0.0087	0.0074	0.0045
4	0.0031	0.0000	0.0000	0.0007	0.0032	0.0012
WRMSE					0.0026	0.1354
RSRS		0.0518	0.0320	0.0218	0.0009	0.0521
APS					6.7E-06	0.0103

Predicted probability for making trips in the West using model estimated on East data

Trips	Observed Probability	Predicted probability for making trips: Transferred Scaled Model n = 500	n = 1000	n = 1500	n = 11296*	Directly Transferred Model n = 11296*
0	0.8387	0.9524	0.9147	0.9075	0.838	0.8254
1	0.1091	0.0605	0.0702	0.0757	0.1095	0.1212
2	0.0441	0.0141	0.0151	0.0148	0.0444	0.0461
3	0.0059	0.0000	0.0000	0.0007	0.0059	0.0054
4	0.0018	0.0000	0.0000	0.0013	0.0018	0.0017
5	0.0005	0.0000	0.0000	0.0000	0.0004	0.0003
WRMSE					0.0054	0.0412
RSRS		0.1274	0.0904	0.0821	0.0009	0.0181
APS					2.9E-05	0.0017

Predicted probability for making trips in Scarborough using model estimated on Toronto data

Trips	Observed Probability	Predicted probability for making trips: Transferred Scaled Model n = 500	n = 1000	n = 1500	n = 6203*	Directly Transferred Model n = 6203*
0	0.7954	0.7839	0.7915	0.7904	0.7949	0.856
1	0.1398	0.1601	0.1494	0.1420	0.1401	0.1083
2	0.0540	0.0460	0.0491	0.0576	0.0542	0.0318
3	0.0076	0.0060	0.0070	0.0073	0.0076	0.0027
4	0.0032	0.0040	0.0030	0.0027	0.0032	0.0012
WRMSE					0.0013	0.2029
RSRS		0.0247	0.0115	0.0066	0.0006	0.0720
APS					1.7E-06	0.0412

Table 4.8 (cont'd) Predictive ability of the transferred scaled model

Predicted probability for making trips in East York using model estimated on Toronto data

Trips	Observed Probability	Predicted probability for making trips: Transferred Scaled Model n = 500	n = 1000	n = 1500	n = 2309*	Directly Transferred Model n = 2309*
0	0.8480	0.8564	0.8426	0.8503	0.8474	0.8684
1	0.1018	0.1071	0.1112	0.1055	0.1020	0.0993
2	0.0446	0.0305	0.0422	0.0409	0.0449	0.0288
3	0.0048	0.0000	0.0030	0.0027	0.0048	0.0024
4	0.0009	0.0000	0.0010	0.0007	0.0009	0.0011
WRMSE					0.0017	0.1079
RSRS		0.0179	0.0112	0.0061	0.0007	0.0260
APS					2.8E-06	0.0012

Predicted probability for making trips in Etobicoke using model estimated on Scarborough data

Trips	Observed Probability	Predicted probability for making trips: Transferred Scaled Model n = 500	n = 1000	n = 1500	n = 4177*	Directly Transferred Model n = 4177*
0	0.7793	0.8251	0.8060	0.8033	0.7781	0.7847
1	0.1434	0.1170	0.1247	0.1263	0.1442	0.1461
2	0.0651	0.0540	0.0593	0.0611	0.0655	0.0576
3	0.0084	0.0040	0.0080	0.0080	0.0084	0.0081
4	0.0026	0.0000	0.0010	0.0007	0.0026	0.0029
5	0.0012	0.0000	0.0010	0.0007	0.0012	0.0005
WRMSE					0.0030	0.0457
RSRS		0.0543	0.0332	0.0298	0.0015	0.0097
APS					8.7E-06	0.0021

* full data set

WRMSE = wieghted root mean square error

RSRS = root of sum of residual squared

APS = aggregate prediction statistic

note: observed and predicted probabilities may not add to 1 due to rounding error residual squared, it is observed that the predictive performance of the updated model improves with increased sample size. In other words, the larger the sample for updating the transferred model, the better the predictive ability of the transferred model. The percentage improvement in the prediction results is non-linear.

A comparative analysis of the transferred scaled (updated) model and the directly transferred model by means of three transferability measures defined in section 4.4 were used to assess the predictive accuracy of the transferred scaled model (Table 4.8, columns 6 and 7). The measures are weighted root mean square error, the root of sum of residual squared and aggregate prediction statistic. Note that in Table 4.8, the predicted probability for making some trips is zero. The reason is that the updated scaled transferred model cannot predict any response level not in the data used in updating. It is therefore assumed that for these response levels, the predicted probability is zero.

Two of the three measures, weighted root mean square error and the root of sum of residual squared, show that the transferred scaled model performs better than the directly transferred model in prediction mode. At a significance level of 0.05, the null hypothesis that the observed probabilities in all the application contexts were generated by the two transferred models cannot be rejected according to the aggregate prediction statistic.

On a regional basis, the transferred scaled model performs best when it was transferred from Toronto to Scarborough, and worst when it was estimated on the East data and transferred to the West, according to the weighted root mean square error measure. Note that by the same measure, the predictive performance of the directly transferred model is better for the East-West regions pair than when it was transferred from Toronto to

Scarborough. These results may suggest that in transferring a model estimated on data from the urban core to the periphery, the transferred coefficients may have to be updated in order to improve the prediction accuracy of the transferred model. Based on the root of sum of residual squared, the transferred scaled model gives reasonably accurate prediction of the aggregate choice probabilities in all application contexts.

The aggregate prediction statistic supports model transferability in all regions at a significance level of 0.05. All the values of the calculated transferred pseudo R^2 are negative, suggesting that the transferred scaled model is not better than a model developed and estimated in the application context, for all of the examples.

4.8 CONCLUSIONS

The purpose of the chapter has been to investigate the spatial transferability of the ordered response model of shopping trip generation. The two main objectives were to assess the performance of direct model transfer without updating the transferred coefficients, and the performance of a scaling updating procedure that adjusts the model parameters.

The results of the study indicate that the direct model transfer performs quite well. The use of a scaling updating procedure substantially improves the predictive ability of the transferred model. In terms of the actual predicted aggregate probabilities, direct model transfer (without updating the coefficients from the estimation context) generally under-predicts the probability for making one or more trips by a relatively large margin. Based on the weighted root mean square error, root of sum of residual squared and aggregate prediction statistic, updating the transferred model using the scaling method significantly improves the prediction accuracy in the application context.

Direct model transfer without updating has the advantage of eliminating any costs for collecting new data on households and travel behavior in the application context. Updating the coefficients of the transferred model has the benefit of improved prediction performance. Clearly, there is a trade-off between cost savings and model transfer effectiveness. Despite the relatively good performance of the directly transferred model in this study, updating the transferred model offers the potential for substantially improved model effectiveness at a relatively small cost.

A problem with the updated transferred, scaled, ordered response model is that in prediction mode, it predicts for only the observed response levels in the new data set for updating the transferred model. Thus if the maximum number of trips made in the new data set is 4, the transferred scaled model can predict only up to 4 trips. Despite this limitation, the transfer scaling approach to adjust the coefficients from the estimation context greatly improves the transfer effectiveness of the ordered response model.

CHAPTER 5

CONCLUSIONS

5.1 INTRODUCTION

This chapter contains a summary of the dissertation, its major contribution to knowledge, and some directions for further research. The summary covers the purpose of the dissertation, the issues investigated, the data and model used, and major findings. Directions for future work are put into two categories: research on accessibility, and on spatial transferability of the model used.

5.2 SUMMARY OF DISSERTATION

This research is a move towards improved trip generation models that are responsive to locational factors and accessibility, and that can be transferred from one spatial context to another with little or no cost. The performance of a directly transferred model and the impact of the scaling updating technique for the transferred coefficients are the two things that were evaluated in the spatial transferability analysis.

Three separate analyses were performed, two of them focusing on the effects of location and accessibility on shopping trip generation. The third analysis was on spatial transferability of the model used. The model used in all the analyses is an ordered response model, a type of discrete choice model that maintains the ordinal nature in the dependent variable in choice situations where there are more than two responses. The analyses were confined to the Greater Toronto Area (GTA).

The analysis on the effect of geographic location was performed for five planning districts in the GTA, two of which are within the older urban area and the remaining three of which are recently developed suburbs superimposed on older towns. Evaluation of the effect of accessibility was limited to Metropolitan Toronto, due to lack of data on the number of people employed in retail establishments in other parts of the GTA. Effects of accessibility on trip generation were analyzed using the data set for Metropolitan Toronto. Separate analyses were also performed for each of the 16 planning districts in Metropolitan Toronto, and for its the core and periphery areas. The study area for the transferability analysis is also Metropolitan Toronto, but a different sub-areas were employed.

The research concentrated on weekday, home-based shopping trips for two reasons: lack of data on shopping trips made on the weekend and a better behavioral interpretation of the results. The level of analysis was the household.

Data on socio-economic characteristics and the geographic location of households, number of people employed in the retail industry and network travel times were employed in the analyses. The number of people employed in retail establishments and the network travel times were used to derive accessibility measures from the gravity model at the traffic zonal level. Three separate analyses were performed, one analysis to examine the effects of geographic location on shopping trips generation, another to assess the impact of accessibility measures on this type of trip, and lastly, to evaluate spatial transferability of the ordered response model.

The effects of geographic location and accessibility were assessed by asymptotic t-statistics. Additionally, a comparative analysis of the predictive ability of a model with and without geographic location or accessibility as an explanatory variable was performed. The impacts of directly transferring the model, and of a scaling updating technique were evaluated by two measures of aggregate prediction errors (weighted root mean square error and root of sum of residual squared), and two test statistics (pseudo R^2 and aggregate prediction statistic).

Overall, the ordered response model proved to be a very useful methodology for the analysis of trip generation. Other major findings from the analyses are as follows.

Effects of Geographic Location

- Weekday home-based shopping trip generation is sensitive to location of households.
- Without location effects, trips in the central city are overpredicted while those in the suburbs are underpredicted.

Effects of Accessibility

- All the accessibility measures were found not to be statistically significant in trip-making decisions of households in Metropolitan Toronto as a whole, in the core and in the periphery.
- The estimated coefficients of all the accessibility indices for Metropolitan Toronto as a whole, its core and its periphery have negative signs.
- Six planning districts have the estimated coefficients of some accessibility measures to be positive but not all of them are significant.

Spatial Transferability Analysis

- Direct transfer of the ordered response model (without any updating of the transferred coefficients) performs reasonably well in predicting the probabilities for making trips in the application context.
- Scaling updating of the transferred coefficients significantly improves the predictive performance of the ordered response model over those of a directly transferred model.

5.3 MAJOR CONTRIBUTIONS

- The research provides a systematic, comprehensive empirical investigation into the effects of locational factors and accessibility on trip generation.
- The good predictive performance of the directly transferred model (without updating the transferred coefficients) challenges the current notion that cross-sectional models cannot provide any good response probabilities in another geographic setting.
- The findings from the scaling updating technique for the ordered response model are new, and are of great significance given the good predictive ability in the application contexts and the scarcity of studies of spatial transferability of trip generation models in general.
- The inclusion of locational factors, and the model used in the analyses, lead to a better understanding of travel behavior when travel is considered as a derived demand, based on people's desire to participate in activities.

5.4 DIRECTIONS FOR FURTHER RESEARCH

A number of research directions emerge from the study. These could be put into two groups: research on accessibility and on model transfer.

Research on Accessibility

Accessibility used in the research was calculated at the traffic zonal level. It would be interesting to use accessibility calculated at the household level in future research which is in line with the trend toward disaggregation in travel demand analysis. A comparison of the effects on travel behavior of accessibility measures derived from different approaches could also be investigated. This could be of great significance to policy-decision making.

Although three hypotheses were put forward to explain the negative values of the estimated accessibility indices, some were not empirically tested. A logical step forward is testing these hypotheses since this is not the first time such a paradoxical effect of accessibility measures in trip generation models has been reported. It will be also interesting to know if there are other types of discretionary trips where accessibility is significant.

Another area that could not be researched in this dissertation but that is of equal importance is the effect of public transport accessibility measures on trip generation behavior of households without a car. A comparative analysis of public transport accessibility measures that reflect the level of service provided by the public transport system in terms of service frequency and zone coverage, and private transport accessibility measures as used in this study, could offer policy makers a wide range of policy options to deal with increased discretionary travel.

This dissertation focused on the relationship between accessibility and shopping trip frequency. It is possible that changes in accessibility levels may have a greater impact on distance travelled than on trip frequency. Future research into the effect of accessibility on total trip length will be of great importance to policy decisions in travel demand.

Research on Spatial Transferability of the Ordered Response Model

Only the scaling updating technique was evaluated for the transferred ordered response model. It would be worthwhile to investigate the effects of other updating procedures such as a Bayesian approach and the joint estimator method developed by Badoe (1994). This will help in deciding which of the updating techniques best enhances the predictive performance of the transferred ordered response model in the application context.

Last but not least, this and other spatial transferability analyses of trip generation models have been limited to cities within the western industrialized world. Validation of the very good performance of the transferred ordered response model (with and/or without any updating of the coefficients) in a developing country context could be investigated. This could reduce the need for large scale transportation surveys which many developing countries are not prepared to commit resources to do.

The results of the empirical analyses presented in this dissertation demonstrate the usefulness of the ordered response model. As well, it would be useful to validate at other locations, using the same model, the conclusion found with these data that accessibility is not an important factor in trip-making decision of households.

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