RESEARCH FUNDED BY THE REGIONAL TRANSIT BOARD THROUGH THE CENTER FOR TRANSPORTATION STUDIES, UNIVERSITY OF MINNESOTA

REGIONAL TRANSIT BOARD

THE ECONOMICS OF ALTERNATIVE TRANSPORTATION MODES: AN EMPIRICAL ASSESSMENT OF THE TWIN CITIES

Barbara J. Kanninen
and Craig Mohn

Sponsored by:
Regional Transit Board

CENTER FOR TRANSPORTATION STUDIES

UNIVERSITY OF MINNESOTA

THE ECONOMICS OF ALTERNATIVE TRANSPORTATION MODES: AN EMPIRICAL ASSESSMENT OF THE TWIN CITIES

Final Report and Executive Summary

Prepared by

Barbara J. Kanninen*

and

Craig Mohn**

May, 1994

Submitted to:

Regional Transit Board
St. Paul, Minnesota

* Barbara J. Kanninen is an assistant professor, Hubert H. Humphrey Institute of Public Affairs, University of Minnesota, Minneapolis.

** Craig Mohn earned an M.P.A. from the Humphrey Institute, University of Minnesota, and is now a Ph.D. student, Department of Agricultural and Resource Economics, University of California, Berkeley.

ACKNOWLEDGEMENTS

This research was supported by a grant from the Regional Transit Board, general funding from the Center for Transportation Studies at the University of Minnesota, and a research fellowship from Resources for the Future, Washington, D.C.

Interim results from this research were presented at the Fourth National Transportation Planning Applications Methods Conference in Daytona Beach, Florida, May 1993 and also at the Annual Research Conference sponsored by the Center for Transportation Studies, in Minneapolis, May 1993. The authors thank attendees of these conferences for the helpful comments and interesting questions they raised.

The authors also thank Mark Filipi and Steve Alderson from the Metropolitan Council for providing us with the 1990 Travel Behavior Inventory data and Matt Welbes for doing preliminary work with the data.

Any errors in this report are the sole responsibilities of the authors.

EXECUTIVE SUMMARY

This report presents a model of travel behavior for the Twin Cities Metropolitan Area using the 1990 Travel Behavior Inventory. The model incorporates mode choice and the number of trips individuals take. Using the estimation results, we report estimates for mode share price elasticities and find that they are quite low. All mode share elasticities are less than 0.25 which means that a 4% price change could cause no more than a 1% change in mode share. Mode share elasticities for non-work trips are higher than those for work trips indicating that there is greater flexibility in non-work trip mode choices than in work trip choices.

Two pricing policy simulations are performed and the results verify that there is low mode choice responsiveness to price changes. The welfare costs associated with these policies are derived. It is found that a 10% gasoline tax would cost the average traveler $0.33 per day. A transit fare reduction by one-half would benefit the average traveler $0.12 per day. It should be noted though that the transit fare reduction affects only a small part of the population who, apparently, receive large cost savings. Although the transit fare reduction does not reduce vehicle use by much, it does increase the transit share by 24%, a substantial increase in ridership. The results presented here imply that large price changes are necessary to induce people to reduce their vehicle use either by switching modes or reducing the number of trips they take.

Using the mode choice model, we also derive values of travel time for different subpopulations in the Twin Cities Metro Area. We find that the average value of travel time for work trips, for all travelers, is $3.65 which is roughly equal to one-half the wage rate, the commonly accepted value. We find that individuals living in the suburbs have higher values of travel time for

work trips than those living in the urban areas, and males have higher values of travel time for work trips than females.

The value of travel time for non-work trips is essentially zero, indicating that individuals receive disutility from their work travel but not from their non-work travel. This finding, in association with the mode share elasticities, has significant policy implications. Mode choices for non-work trips are more flexible than mode choices for work trips, and individuals place a high value on travel time for work trips while they do not for non-work trips. These two results imply that a policy focus on reducing vehicle use for non-work trips could have a greater impact, at lower cost to the traveler, than a policy focus on work trips.

TABLE OF CONTENTS

LIST OF TABLES

1. INTRODUCTION

Transportation congestion is worsening in most U.S. cities. In addition to the opportunity costs of time associated with traffic congestion, there are environmental costs associated with automobile use: greenhouse gas emissions, air, water and noise pollution, and increased land-use. Yet people seem to be increasingly unwilling to use alternative modes of transportation, such as public transit, carpools, or bicycles, which might impose lower environmental and time costs on society. Nationally, the automobile occupancy rate during commute hours was 1.1 in 1990 (Krupnick 1992). Although the Twin Cities does not face the severe congestion and pollution problems faced by cities such as Los Angeles and New York City, it is nevertheless important to begin addressing environmental problems in medium-sized cities.

In economic terms, the problem with automobile use is that the full social costs outweigh the benefits. Clearly, policies that discourage single-occupancy automobile use in favor of carpooling or mass transit can reduce the externality costs associated with transportation use. But policies that discourage automobile use tend to inconvenience travelers, reducing the benefits they derive from travel. In this report, the use of pricing policies to discourage automobile use is investigated in order to learn about how responsive people are to altering their behavior. We estimate a model that explains mode choice and number of trips for individuals in the Twin Cities Metropolitan Area based on the 1990 Travel Behavior Inventory. Using this model, we can derive price elasticities and the value of travel time. This is the type of information needed to responsibly design environmental policies for transportation.

In this report, we focus on the search for policies that improve the overall efficiency of the transportation system. The report is outlined as follows: section 2 discusses economic issues associated with environmental policies for transportation; section 3 discusses the econometric model, the data and variables used in this analysis; section 4 discusses model estimation results, the results of two pricing policy simulations and the value of travel time; and section 5 presents conclusions.

2. ENVIRONMENTAL POLICIES FOR TRANSPORTATION

This section reviews economic issues associated with the development of environmental policies for transportation and demonstrates that pricing policies can be appropriate mechanisms for effectively reducing emissions. In subsection 2.1, the concept of environmental externalities are discussed. In subsection 2.2, the concept of economic efficiency is introduced and is argued to be an appropriate policy goal. Subsection 2.3 discusses the economics literature on transportation and environmental policy and concludes that pricing policies are one of several potentially effective environmental policies for transportation. But in order to measure the potential effectiveness of pricing policies, we need reliable information about travel behavior..

2.1 The Social Cost of Driving

According to economists, the problem with automobile use is that automobile users do not pay for the time delay and environmental costs they impose on others. The costs of automobile use can be divided into two categories: private costs and public (external) costs. Private costs are those actually borne by the driver and consist of gasoline costs, parking fees, road tolls, wear and tear on the automobile and the opportunity cost of travel time. External costs include congestion costs (the increased time spent by others on the road as a result of the marginal increase in congestion created by an additional car), air, water and noise pollution, increased risk of traffic accidents and increased deterioration of the roads. The sum of private and public costs is the full social cost of driving. Individuals weigh their own, private costs against the benefits they anticipate from driving to determine how much driving they will do. Because their driving produces external costs, the result is a market inefficiency where total social costs exceed total (mostly private) benefits. A recent estimate suggests that time delay costs alone exceed $22 billion annually (Hanks and Lomax 1991).

2.2 The Economics of Environmental Policy for Transportation

The primary purpose of the surface transportation system is to move as many people as possible to and from where they want to go. But because the surface transportation system as a whole harms the environment, this purpose seems to be directly at odds with the environmental goal of reducing emissions.[1] The challenge for transportation / environmental policymakers is to design a set of policies that will effectively reduce emissions while still allowing the transportation system to operate efficiently. A basic concept in economics is that the best way to pursue a policy goal is to target that goal directly (Baumol and Oates 1988). In the case of transportation policy, we seem to have two opposing goals: to move people as efficiently as possible given the present transportation infrastructure (technological efficiency) and to reduce transportation-related externalities (economic efficiency).

Ideally, the notion of moving people as efficiently as possible would incorporate both goals simultaneously. Efficiency implies least cost, and if we forced people to pay the full cost of driving,

[1] The nation's surface transportation system presently contributes 70% of carbon monoxide (CO), 39% of nitrogen oxides (NO_x), and 30% of volatile organic compound (VOC) emissions (USEPA 1992). In urban areas that violate the National Ambient Air Quality Standards (NAAQS) the shares of automotive emissions are even higher.

we would indeed obtain an efficient solution that balances the benefits associated with automobile use with the full social costs, including congestion and environmental externalities (Baumol and Oates 1988). But the present system is far different from this economically ideal world. People do not pay the full cost of their driving and it is not clear that they will do so anytime soon.[2]

In our non-ideal world, it makes sense to pursue the goals of technological and economic efficiency using a mix of policies where each goal is targeted directly using the appropriate mechanism. In other words, the idea of getting more people where they want to go faster than before is a public benefit.[3] The fact that at present, people are not paying for the costs they impose on society when they drive generates a large public cost. These costs must be addressed using appropriate policies.

2.3 Literature Review of Environmental Policies for Transportation

There is a growing literature evaluating emissions-related policies including reformulated gasoline, enhanced inspection and maintenance programs, alternative fuels, congestion pricing, gasoline taxes and accelerated vehicle scrappage programs (Alberini et al. 1993, Geoghegan et al. 1994, Harrington et al. 1994, Krupnick 1992, Krupnick et al. 1993, Walls 1992). Harrington et al. (1994) find that, in general, policies that rely on economic incentives, such as emissions rate-based vehicle registration fees and gasoline taxes; and target high emissions rates, such as vehicle inspection and maintenance programs; are more cost-effective than technology-based policies, such as alternative

---

[2] There has been increased interest in the idea of congestion pricing which would charge drivers for the congestion externality they impose. The Intermodal Surface Transportation Act (ISTEA) of 1991 includes funding for congestion pricing pilot projects. At present though, there is only one pilot project underway (in the San Francisco Bay Area) and it may be years before implementation occurs.

[3] Small (1992, pp. 36-45, 77) suggests that travel time for work trips is typically valued at 50% of the wage, or approximately $4.80 per hour for the U.S. in 1989. See Table 9 for value of travel time estimates for the Twin Cities.

fuel vehicles and California emissions standards.

If we are interested in targeting automobile-related emissions we must design policies that create the appropriate incentives. The cost-effectiveness of a program depends crucially on the ability of a program to target high-emitting vehicles, especially those that are heavily used. In addition, to maximize benefits, it is important to focus on critical areas, at critical times of day, during critical seasons. It may be impossible to develop one program to satisfy all of these criteria at once, but it is clear that certain programs are more likely to create the appropriate incentives for high-emitting vehicle owners. For example, Harrington et al. (1994) recommend an emissions rate-based vehicle registration fee coupled with a VMT-based fee, which would focus both on emissions rates and amount of vehicle use and encourage owners of these vehicles to maintain them properly and/or drive less.

Pricing policies such as gasoline taxes and congestion pricing are advocated by economists because they directly target externalities by increasing the privately borne costs of automobile use. Gasoline taxes, however, do not focus on congested areas and times and therefore might result in more diffuse emissions and congestion reductions that might not bring large marginal benefits (Krupnick et al. 1993). Congestion pricing is primarily intended to reduce congestion costs but also has the benefit of reducing the higher VOC emissions associated with congested conditions. Recent empirical work by Geoghegan et al. (1994), Mohring and Anderson (1994) and Repetto et al. (1991) has shown that optimal congestion fees can substantially reduce congestion and emissions costs and produce significant public benefits.

It will be important when designing environmental policies for transportation, such as those mentioned above, to understand the implications of these policies on transportation users. We must have a sense of the expected changes in travel behavior that will occur in order to adequately measure and predict the expected costs (such as dollar outlays, time and inconvenience) and the expected benefits (such as reduced congestion and emissions). The research presented here focuses on how expected travel cost and travel time change individual behavior. It also presents the welfare costs associated with two possible environmental pricing policies that discourage automobile use: a gasoline tax increase and a transit fare reduction. In the following section, the econometric model used for this analysis is presented.

3. AN ECONOMETRIC MODEL OF TRAVEL BEHAVIOR

This section presents the econometric, behavioral model which incorporates mode choice and number of trips taken. There are, in fact, a multitude of joint, short-run decisions that a traveler makes, including number of trips, destination, route, timing and mode. In addition, households and individuals make longer run decisions including how many automobiles or other vehicles to own and where to live and work. Since this model focuses on only two joint (short run) decisions, it cannot fully predict the implications of pricing or other policies. But it can give a good indication of the relative effectiveness of different policies, especially in the short run. To date, no travel behavior model jointly models all the decision mentioned above.

This section begins by introducing the model, first the mode choice part and then the number of trips part in subsections 3.1 and 3.2. Following this, in subsections 3.3 and 3.4, model procedures for model estimation and policy simulations are discussed. In subsections 3.5 and 3.6, the data and variables used in the model are discussed.

3.1 Mode Choice Model

Suppose we have a set of n individuals with utility functions represented by:

$$U_{itm} = V_{itm} + \epsilon_{itm} \tag{1}$$

where subscript i indicates the individual, subscript t indicates the particular trip taken by individual i and subscript m indicates the travel mode used ($m \in M$ = {car alone, carpool, transit} in the empirical example presented here).

This is the random utility model where utility has an observable component (V_{itm}) and an unobservable (random) component (ϵ_{itm}). We specify the observable component V_{itm}, to be:

$$V_{itm} = \alpha_m + \beta_m x_{it} + \gamma x_{itm} \tag{2}$$

where the matrix x_{it} contains variables that are specific to the individual or trip (income, age, gender, trip purpose, for example) and x_{itm} contains variables that, in addition to being individual- and trip-specific, are also mode-specific (expected trip cost, expected travel time). This specification requires mode-specific coefficients (β_m's) for the different individual and trip characteristics because the model we estimate requires the variable to vary over an individual's mode choices.[4] There will also be alternative-specific constants to capture the unexplained part of the underlying probabilities associated with each mode. The variables of most interest in this study, expected trip cost and travel time do not take mode-specific coefficients because these variables do vary over mode choices. We can use the coefficients on cost and time to calculate price elasticities as well as the value of travel time.

[4] By using mode-specific coefficients, we are effectively multiplying each variable by dummy variables representing the specific modes. This has the effect of creating variables that vary over mode choices.

If we assume that the error terms, ϵ_{itm}, are independent and identically distributed following the Gumbel distribution[5] with scale parameter μ, then it can be shown (see Ben-Akiva and Lerman 1985) that mode choice is represented by the multinomial logit model where the probability that individual i (on trip t) uses mode m is:

$$P_{itm} = \frac{e^{\mu V_{itm}}}{\sum_{k \in M} e^{\mu V_{itk}}} \tag{3}$$

The denominator of P_{itm} is summed over all modes within the set of modes, M. The parameter μ is unidentifiable and is arbitrarily (and innocuously) set equal to one.

With the multinomial logit model, the mode-specific coefficients (β) in V_{itm} are not all identifiable. Standard practice is to normalize the coefficients so that β_0 is equal to zero, where one of the mode choices is arbitrarily chosen to be mode 0 (in our model this mode is typically carpool). This makes the coefficient values in V_{itm} difficult to interpret. The sign of β_m indicates the regressor's impact on the probability of choosing mode m relative to mode 0. But we must also look at the magnitude of β_m when comparing the regressor's impact on any other mode to that of mode m. Interpretations of coefficient estimates are discussed in Section 4.

The model specified in equations 1 through 3 assumes that individuals make mode choices for each trip independently. That is, it assumes that the error terms in equation 1 are independent for all individuals and trips. A more appropriate assumption would allow individuals to have some

---

[5] The Gumbel distribution is specified because of its properties, namely that the difference between two independent, Gumbel-distributed random variables with the same scale parameter is distributed logistically and that the maximum of two Gumbel-distributed random variables with the same scale parameter is distributed Gumbel. These properties facilitate the derivation of the multinomial logit model Furthermore, the Gumbel distribution is an approximation to the normal distribution.

underlying propensity to choose certain modes more or less often than others, and would therefore allow correlation among an individual's mode choices. By not allowing for this correlation, we obtain inefficient, and possibly inconsistent, parameter estimates. Kanninen (1994) addresses this problem by estimating models with fixed and random effect error terms. These models are highly complex and computer intensive, and have not been used before in mode choice models. In this report, the standard approach is employed where all error terms are assumed to be independent. To account for the multiple observations available for some individuals (because of the number of trips taken), weighted estimation is performed where the weight for each observation is equal to the inverse of the number of trips an individual took.

3.2 Number of Trips Model

Because mode choice is an integral part of the trip-making decision, a more complete model of travel behavior must take both mode choice and number of trips decisions into account. Because of the simultaneity of these two decisions, we cannot adequately model them as separate equations[6] But we also cannot use the actual mode choices in the number of trips regression because that would bias the estimation due to correlation between the mode choice and the error term in the number of trips equation. Instead, we include a kind of instrumental variable that represents mode choice but is independent of the error term. The instrumental variable used in our model is the "inclusive value" which is equal to the log of the denominator of equation 3:

[6] Train (1980) has shown that these decisions must be modeled jointly.

$$IV_i = \log\left(\sum_{m \in M} e^{\mu \hat{V}_{itm}}\right) \tag{4}$$

This variable represents the expected utility the individual obtains from the mode choices available for the particular trip taken and is expected to be positively correlated with the number of trips taken.

Number of trips takes only discrete values (0,1,2,...), and is generally clustered around the low integers. For these reasons, many researchers use the poisson distribution to model number of trips. The poisson distribution can be expressed as:

$$f(y_i) = \frac{e^{-z_i\beta}\,(z_i\beta)^y}{y!} \tag{5}$$

where y_i represents the number of trips taken by individual i and z_i represents the matrix of explanatory variables that may contain individual-specific variables (including those in x_{it},) and also includes the inclusive value. Note that trip-specific variables cannot enter this part of the model since this decision is modeled at the individual level rather than the trip level. Equation 5 is estimated using maximum likelihood estimation.

3.3 Estimating the Joint Model

The appropriate procedure for the joint estimation of the two decisions is Full Information Maximum Likelihood (FIML). The log-likelihood function is:

$$\ln L = \sum_{i=1}^{n}\left\{\left[\sum_{t=1}^{T_i}\sum_{m=1}^{M} I_{itm}\ln P_{itm}\right] + f(y_i)\right\} \tag{6}$$

where T_i represents the number of trips taken by individual i and I_{itm} is an indicator variable that equals 1 when individual i used mode m for trip t. Unfortunately, FIML is an extremely computer-intensive procedure. Practitioners therefore often resort to using a sequential estimation procedure that facilitates estimation and provides consistent, but inefficient estimates. The first step of the sequential procedure is to estimate mode choice using the *conditional* probability of equation 3 (conditional on the number of trips taken). The results of this model allow us to estimate inclusive values for each individual, which are then included in the poisson regression for number of trips taken.[7]

3.4 Empirical Policy Analysis

The pair of equations described above (probabilities of mode-choice and number of trips) can be used for pricing policy simulations as follows. We calculate predicted probabilities for the mode choice decisions and sum these probabilities over all individuals to obtain the predicted number of individual trips taken via each mode. The predicted probabilities are:

$$\hat{P}_m = \sum_{i=1}^{n} \sum_{t=1}^{T(i)} \hat{P}_{itm} \tag{7}$$

Provided our estimation procedures give us unbiased estimates of the coefficients, the predicted number of trips in each category will match the actual number. We can then simulate a change in trip cost and obtain new predictions for the probabilities associated with each mode. We

[7] The problem with this sequential procedure is that information is only being passed through the system in one direction; estimation of mode choice influences estimation of the number of trips decision but not vice-versa. This problem would be avoided by using FIML, the approach taken in Kanninen (1994).

can also predict new inclusive values which can be used in the number of trips equation to predict the total change in travel behavior and vehicle use.

Part of this procedure involves calculating the new inclusive value, or expected utility value, for each individual. Since we include a cost variable in the mode choice model, we have an estimate for the marginal utility of a dollar (equal to the coefficient on cost, β_{cost}). The inverse of β_{cost} can be used to convert the expected utility measure from utility terms to dollar terms (Small 1992, p.22). The welfare measures for each individual and trip can be expressed as:

$$W_i^B = \frac{\ln \sum_{m \in M} e^{\mu \hat{V}_{itm}^B}}{\beta_{cost}} \tag{8}$$

$$W_i^A = \frac{\ln \sum_{m \in M} e^{\mu \hat{V}_{itm}^A}}{\beta_{cost}} \tag{9}$$

where B and A are indexes representing Before and After price change conditions. These measures can be multiplied by the associated, predicted number of trips (before and after the price change) to obtain the full welfare change each individual experiences due to the price change:

$$\Delta \hat{W}_i = \hat{W}_i^B \hat{T}_i^B - \hat{W}_i^A \hat{T}_i^A \tag{10}$$

The overall welfare cost is estimated by taking the mean of ΔW_i.

3.5 The Data

The data we use to estimate this model comes from the 1990 Travel Behavior Inventory of the Twin Cities Metropolitan Area, collected by the Metropolitan Council. This data set has a sample size of 24,511 individuals in 9746 households. All individuals over 5 years of age in each household recorded one-day travel diaries with information on every trip segment taken in a motorized vehicle during that day. We therefore have trip data on mode choice, travel time and individual and household demographic characteristics.

Data from three households were dropped due to internal inconsistencies. We removed all data for people who declined to provide relevant information including age, approximate income, employment or student status, or information as to possession of a drivers license. We also discarded those who omitted trip segments, gave destination addresses which were incorrect, or reported unrealistic time and distance combinations. Furthermore, each trip segment does not entail a new, independent mode choice, because if an individual leaves home driving a car, subsequent transportation decisions will likely involve the car. We identified two points at which most people will make mode-choice decisions: home and work. Trip segments were chained together so that every trip which was not the first or last of the day both began and ended at either home or work. These trip-chains, which are more reflective of the actual decisions made, often involved multiple purposes. For the purposes of this study, any trip which contained a segment using bus transit was classified as a bus trip, so that "park-and-riders" were considered to have chosen the bus. Similarly, trips which contained a segment involving multiple passengers in a car were classified as carpool trips, because most carpool trips involve an initial or final segment which has an unaccompanied driver.

Our final analysis was restricted to trips taken by those 16 years of age and older, and included 31,954 trip-chains. Of these individuals, 23.8% recorded no trips and the remaining averaged 4.25 trips per day.

Some characteristics of individuals and trips are presented in Tables 1 and 2.

3.6 Descriptions of Variables

Definitions of the explanatory variables used in estimation are listed in Table 3.

TABLE 1: TRIP PURPOSES

Characteristics	Went Home	Went to Work	Work Task	Went to School	Drop Off Another	Go to Trans-port	Go to Shop-ping	Other
Average Dist-ance	5.8 miles	8.3 miles	6.8 miles	3.9 miles	4.5 miles	6.1 miles	4.1 miles	5.1 miles
Average Time	16.3 minutes	19.0 minutes	17.6 minutes	17.4 minutes	12.5 minutes	18.0 minutes	12.6 minutes	14.5 minutes
% by Car	92.5%	96.5%	97.0%	40.2%	99.3%	63.4%	99.2%	97.7%
% by Bus	7.1%	3.0%	1.2%	59.0%	7.7%	33.2%	0.7%	2.0%
% of all trips	35.7%	14.6%	4.3%	4.1%	7.3%	0.4%	11.6%	21.8%
% during peak hours	28.8%	43.6%	23.4%	72.4%	0.6%	40.0%	20.5%	25.0%

TABLE 2: CHARACTERISTICS OF TRANSPORTATION USERS

Characteristics	Those who bike/walk to work	Bus Riders	Whole Population
Average Age	32.7	35.6	36.3
% Female	40.6%	57.5%	50.8%
Average Household Income	$42K	$42K	$47K
% Urban	55.3%	51.2%	21.3%
Average Household Size	3.2%	3.0%	3.4%
Average Vehicles in Household	1.9	1.7	2.3
Average Daily In-Vehicle Time	30.3 minutes	82.8 minutes	63.5 minutes
Average Daily In-Vehicle Distance	10.3 miles	21.7 miles	24.3 miles
% Peak Hour Travel	29.1%	43.9%	33.4%

TABLE 3: VARIABLES USED IN MODELS

Mode Choice Model

alone	-	alternative-specific constant on car alone
bus	-	alternative-specific constant on transit
peak	-	dummy for travel during 7 an 9 am or 4 and 6 pm
downtown	-	dummy for trip destination in either downtown Minneapolis or St. Paul
cost	-	expected out of pocket cost of trip including gasoline cost, parking cost and/or transit fare
time	-	expected travel time multiplied by the derived wage rate which equals the household per capita income divided by the number of hours worked
male	-	dummy variable for male
worktrip	-	dummy variable for trips involving travel to/from work
shoptrip	-	dummy variable for trips involving travel to/from shopping
dollars	-	household income in thousands of dollars
frcar	-	fractional car availability in household, defined as the number of vehicles divided by the number of persons in the household
urban	-	dummy variable for residence in Minneapolis or St. Paul

Number of Trips Model

constant	-	intercept term
incval	-	inclusive value from lower level (mode-choice) multinomial\ logit model
male	-	dummy variable for male
dollars	-	household income in thousands of dollars
age	-	age of individual
frcar	-	fractional car availability in household, defined as the number of vehicles divided by the number of persons in the household
urban	-	dummy variable for residence in Minneapolis or St. Paul
wrk_ctr	-	dummy variable for people who work downtown (Minneapolis or St. Paul)
hom_ctr	-	dummy variable for people who live downtown
kids	-	number of children in household
multijob	-	dummy variable for individuals who have more than one job
h_size	-	number of people in household

4. ESTIMATION RESULTS AND POLICY SIMULATIONS

4.1 Mode Choice Model

Coefficient estimates for the mode choice and number of trips models are presented in Table 4. Mode choice consists of three categories: car alone, carpool (driving or riding with at least one other passenger) and transit. Since, as discussed in section 3, the coefficients for the individual and trip-specific variables for the three mode choices are not all identifiable, they are normalized to zero for one mode; in this case, the carpool coefficients are typically chosen for normalization. Mode-specific coefficients are indicated by the mode specified in parentheses.

The results indicate that people are more likely to use transit during peak hours and when going downtown. The transit share of trips going downtown during peak hours is 15% compared to a 2.5% share of all trips. This phenomenon is probably, to some extent, a function of the convenient transit routes to the downtown areas, especially during peak hours, as well as the higher parking prices that discourage vehicle use.

Males are more likely to drive alone than carpool and more likely to carpool than use transit (Females have almost a 4% transit share while males have a 2.2% share).

People are more likely to drive alone or use transit for work trips. Work trips downtown have a larger transit share and lower single-occupancy vehicle share. Work trips to other destinations, however, are highly likely to be single-occupancy due, presumably, to the large number of unique suburb-to-suburb commutes. Shopping trips are more likely to be carpool than single-occupancy or transit.

Higher income households are more likely to drive alone or carpool. In addition, car availability, as indicated by the variable "frcar," makes a person more likely to drive alone or carpool than use transit, as expected.

People in the urban areas are less likely to drive alone and more likely to use transit than people in the suburbs.

The coefficient on expected cost is negative, as expected, meaning that automobile pricing policies can be used to reduce vehicle use. The time coefficient, however, is insignificant in this model.[8]

4.2 Number of Trips Model

Coefficient estimates for the number of trips model, for those who took trips, are presented in Table 5. The coefficient on the inclusive value, or expected utility from the mode choice model, is positive, as expected. Variables that tend to increase the number of trips an individuals takes are "urban" and "household size." Variables that tend to decrease number of trips are "male," living or working downtown, number of children and "has multiple jobs."

---

[8] Time in this model is equal to trip time multiplied by the individual's wage rate. The value of time calculations presented later in this report are based on mode choice models that use trip time alone as the time variable.

TABLE 4: MODE CHOICE COEFFICIENT ESTIMATES

Variable	Coefficient Estimate[9]	T-statistic
Constant (car alone)	-1.21 **	-23.15
Constant (transit)	-1.87 **	-14.03
Peak (car alone)	0.40	1.55
Peak (transit)	0.62 **	7.73
Downtown (car alone)	-0.19 **	-3.56
Downtown (transit)	1.96 **	22.55
Cost	-0.25 **	-14.66
Time	-0.000037	-0.15
Male (car alone)	0.49 **	19.32
Male (transit)	-0.24 **	-2.97
Worktrip (car alone)	0.64 **	27.18
Worktrip (transit)	0.62 **	12.59
Shoptrip (car alone)	-0.16 **	-8.51
Shoptrip (transit)	-0.73 **	-7.67
Dollars (car alone)	0.014 **	6.47
Dollars (transit)	0.014 **	6.93
Frcar (car alone)	1.93 **	37.65
Frcar (transit)	-1.81 **	-12.71
Urban (car alone)	-0.031	-1.05
Urban (transit)	1.13 **	13.9

[9] ** indicates statistical significance at the 5% level. * indicates statistical significance at the 10% level.

TABLE 5: POISSON REGRESSION ON NUMBER OF TRIPS

Variable	Coefficient Estimate[10]	T-statistic
Constant	1.28 **	30.87
Incval	0.068 **	4.20
Male	-0.039 **	-3.07
Dollars	0.00060	1.61
Age	0.00048	1.16
Frcar	-0.049	-1.50
Urban	0.044 **	3.41
Hom_ctr	-0.44 **	-3.33
Wrk_ctr	-0.067 **	-3.22
Kids	-0.19 *	-1.77
Multijob	-0.33 **	-4.58
H-size	0.035 **	6.51

[10] ** indicates statistical significance at the 5% level. * indicates statistical significance at the 10% level.

4.3 Pricing Policy Simulations

Using the model presented in the previous section, we can simulate mode choice and number of trips changes that would occur if we changed the relative prices of the modes available. The examples presented here will be a 10% increase in the price of gasoline and a 50% reduction in the price of transit. Both of these price changes are expected to increase transit use and reduce automobile use. Note that the gasoline price increase encourages both transit and carpooling (because both are lower cost than single-occupancy automobile use) while the transit price reduction encourages transit use only (discouraging, in a relative sense, automobile use).

Tables 6 a-c present the predicted mode share elasticities. The mode share elasticities represent the percentage changes in the probabilities of choosing each mode relative to a percentage change in the cost used in the scenario. These elasticities are considered partial elasticities in that they are *conditional* on the trip being taken. A full elasticity would account for the probability that a trip might no longer be taken if the price increases. The elasticities reported in tables 6 a-c are quite low, all being less than 0.25. This indicates that price changes would have to be substantial to reduce automobile use.[11] It is useful to note that the elasticities are larger in magnitude for non-work trips than for work trips. This indicates that non-work trips are more flexible than work trips, a finding that has important policy implications.[12]

Tables 7 and 8 report the estimated mode choices, number of trips and welfare costs resulting from policy simulations based on the two pricing policies discussed above. Note that these changes

[11] At least a 4% change in price is required to obtain a 1% change in mode share. Since the transit mode share is less than 3%, this means that a 4% change in price would increase the proportion of people using transit by less than .03%.

[12] Although 75% of all trips are for non-work purposes, most attention (including data collection and policy development) seems to be focused on work trips. But the greater flexibility of non-work trips indicates that we could achieve emissions reductions at lower cost in terms of traveler inconvenience by focusing more attention on reducing these trips.

and costs are predicted only for those individuals that recorded a positive number of trips. The gasoline tax costs the average traveler \$0.33 per day. The transit fare reduction benefits the average traveler \$0.12 per day. It should be noted that the transit fare reduction affects only a small part of the population who, apparently, receive large cost savings. Although the neither policy reduces vehicle use by much, the transit fare reduction does increase the transit mode share by 24%, a substantial increase in ridership.

TABLE 6: MODE SHARE ELASTICITIES

a: All Trips

Mode	Elasticity with respect to an automobile price change (as in a gasoline tax)	Elasticity with respect to a transit price change
Car alone	-0.07	+0.01
Carpool	+0.08	+0.01
Transit	+0.23	-0.24

b: Work Trips

Mode	Elasticity with respect to an automobile price change (as in a gasoline tax)
Car alone	-0.089
Carpool	+0.054
Transit	+0.20

c: Non-Work Trips

Mode	Elasticity with respect to an automobile price change (as in a gasoline tax)
Car alone	-0.22
Carpool	+0.029
Transit	+0.29

TABLE 7: EFFECTS OF A 10% GASOLINE PRICE INCREASE[13]

Trip Decisions	Before tax	After tax
% Car alone	59.9%	59.6%
% Carpool	39.1%	39.3%
% Transit	2.5%	2.6%
Number of trips	4.254	4.249
Welfare cost		-$0.33 per person per day

[13] The estimates presented in this table are based on model predictions and do not add up to 100% exactly.

TABLE 8: EFFECTS OF A 50% TRANSIT FARE REDUCTION[14]

Trip Decisions	Before tax	After tax
% Car alone	59.9%	59.6%
% Carpool	39.1%	38.9%
% Transit	2.5%	3.1%
Number of trips	4.254	4.256
Welfare cost		+$0.12 per person per day

[14] The estimates presented in this table are based on model predictions and do not add up to 100% exactly.

4.4 The Value of Travel Time

The model presented above assumes that the value of travel time is a multiplicative function of an individual's wage rate. That is, individuals who are paid a high hourly wage place a high value on travel time while those who are paid a lower wage or who do not work place lower values on time. It is possible to use the mode choice model to derive the average value of time for different populations using a slightly different approach. If coefficients for travel time (without multiplying travel time by wage rate) and trip cost are estimated in the mode choice model, then we can derive the value of time as follows:

$$\hat{v} = \frac{\beta_{time}}{\beta_{cost}} \tag{11}$$

where β_{time} is equal to the estimated marginal utility of time and β_{cost} is equal to the estimated marginal utility of a dollar, both from the mode choice model.

We can use various subpopulations of individuals or trips to derive varying average values of time for these different subpopulations. Table 9 reports the values of time calculated using various mode choice models that include time and cost (the coefficients for these models are not reported here).

The results indicate that individuals place an average value of $3.65/hour on work trips[15] but a zero value on non-work trips. This indicates that individuals derive disutility from travel to work, but do not derive disutility from non-work travel. This may be because non-work trips are considered part of leisure activities rather than as disutility. Further subdividing work trips, we find that

[15] This is roughly equal to half the wage which is the value of travel time recommended by Small (1992).

suburban households place higher values on work travel times than urban households and males place higher values on travel time than females. Both of these results are consistent with the general economic notion that higher income people place a higher value on travel time.

These findings, in association with the mode share elasticities presented in Tables 6a-c, have significant policy implications. The mode share elasticities indicate that mode choices for non-work trips are more flexible than mode choices for work trips, and these results on the value of travel time indicate that individuals place a high value on travel time for work trips but not for non-work trips. These two results imply that a policy focus on reducing vehicle use for non-work trips could have a greater impact, at lower cost to the traveler, than a policy focus on work trips.

TABLE 9: VALUES OF TRAVEL TIME

Individuals and trips	Value of travel time per hour
All work trips	$3.65 / hour
All shopping trips	~ 0
All other trips	~ 0
All work trips by urban households	$1.24 / hour
All work trips by suburban households	$ 4.15 / hour
All work trips by males	$ 3.65 / hour
All work trips by females	$ 2.91 / hour

5. CONCLUSIONS

This report has presented a model of travel behavior for the Twin Cities Metropolitan Area using the 1990 Travel Behavior Inventory. The model incorporates mode choice and the number of trips individuals take. Using the estimation results, we report estimates for mode share price elasticities and find that they are quite low. All mode share elasticities are less than .25 which means that a 4% price change could cause no more than a 1% change in mode share. Mode share elasticities for non-work trips are higher than those for work trips, indicating that there is greater flexibility in non-work trip mode choices than in work trip choices.

Two pricing policy simulations are performed and the results verify that there is low mode choice responsiveness to price changes. The welfare costs associated with these policies are derived and it is found that a 10% gasoline tax would cost the average traveler $0.33 per day. A transit fare reduction by one-half would benefit the average traveler $0.12 per day. It should be noted though that the transit fare reduction affects only a small part of the population who, apparently, receive large cost savings. Although the transit fare reduction does not reduce vehicle use by much, it does increase the transit share by 24%, a substantial increase in ridership.

Using the mode choice model, we also derive values of travel time for different subpupulations in the Twin Cities Metro Area. We find that the average value of travel time for work trips, for all travelers, is $3.65 while the value for non-work trips is essentially zero. This finding, in association with the mode share elasticities, has significant policy implications. Mode choices for non-work trips are more flexible than mode choices for work trips, and individuals place a high value on travel time for work trips while they do not for non-work trips. These two results imply that a policy focus on reducing vehicle use for non-work trips could have a greater impact, at lower cost to the traveler, than a policy focus on work trips.

The results presented here imply that large price changes are necessary to induce people to reduce their vehicle use either by switching modes or reducing the number of trips they take. It is important to keep in mind, though, that the model presented here includes only two of the many decisions travelers make simultaneously. Travelers jointly determine the number of trips, destination, route timing and mode, as well as the number of vehicles to own and where to live and work (in the longer run). If pricing policies are imposed, we will see larger changes than the ones predicted here because of the additional choices individuals can make about their travel behavior.

REFERENCES

Alberini, A., D. Edelstein, W. Harrington and V.D. McConnell, 1994, "Analysis of Emission Reductions and Cost of the Delaware Vehicle Retirement Program," Resources for the Future Discussion Paper, Washington, D.C.

Baumol, W.J. and W.E Oates, 1988, *The Theory of Environmental Policy*, Cambridge University Press, Cambridge.

Ben-Akiva, M. and S.R. Lerman, 1985, *Discrete Choice Analysis: Theory and Application to Travel Demand*, MIT Press, Cambridge.

Downs, A., 1992, *Stuck in Traffic: Coping with Peak-Hour Traffic Congestion,* The Brookings Institution, Washington, D.C.

Geoghegan, J.A., B.J. Kanninen and C. Mohn, 1994, "Environmental Congestion Pricing: an Empirical Assessment," Resources for the Future Discussion Paper, forthcoming, Washington, D.C.

Greene, W.H., 1993, *Econometric Analysis*, Second Ed., Macmillan, New York.

Hanks J.W., Jr., and T.J. Lomax, 1991,"Roadway Congestion in Major Urban Areas 1982 to 1988," Paper No. 910246, given at 70th Annual Meeting of the Transportation Research Board, Washington, D.C., January.

Harrington, W., M. Walls and V.D. McConnell, " 1994, "Shifting Gears: New Directions for Cars and Clean Air," Resources for the Future Discussion Paper, forthcoming, Washington, D.C.

Kanninen, B.J., 1994, "Estimating Mode Choice and Trip Frequency Decisions Using Travel Diary Data," draft manuscript, Resources for the Future, Washington, D.C.

Krupnick, A.J., 1993, "Vehicle Emissions, Urban Smog and Clean Air Policy," in *The Environment of Oil*, R.J. Gilbert (ed), Kluwer Academic Publishers, Boston.

Krupnick, A.J., M.A.Walls and H.C. Hood, 1993, "The Distributional and Environmental Implications of an Increase in the Federal Gasoline Tax," Resources for the Future Discussion Paper ENR93-24.

McFadden, D., 1973, "Conditional Logit Analysis of Qualitative Choice Behavior," in *Frontiers in Econometrics,* P. Zarembka, (ed.), Academic Press, New York.

McFadden, D., 1978, "Modeling the Choice of Residential Location," in *Proceedings of the International Conference on Spatial Theory,* Bastad, Sweden, North-Holland, Amsterdam.

Mohring H. and D. Anderson, 1994, "Congestion Pricing for the Twin Cities Metropolitan Area," Report to the Met Council, Twin Cities.

Repetto, R., R.C. Dower, R. Jenkins and J. Geoghegan, 1992, *Green Fees: How a Tax Shift Can Work for the Environment and the Economy,* World Resources Institute, Washington, D.C.

Small, K.A., 1992, *Urban Transportation Economics*, Harwood Academic Publishers, Chur, Switzerland.

Small, K.A., C. Winston, and C.A. Evans, 1989, *Road Work: A New Highway Pricing and Investment Policy,* Brookings Institution, Washington, D.C.

Train, K., 1980, "A Structured Logit Model of Auto Ownership and Mode Choice," *Review of Economic Studies*, 47, 357-70.

Train, K,. 1986, *Qualitative Choice Analysis: Theory, Econometrics, and an Application to Automobile Demand,* MIT Press, Cambridge.

United States Environmental Protection Agency, 1992, *National Air Quality and Emissions Trends Report 1991,* Washington, D.C.

Walls, M.A., 1992, "Differentiated Products and Regulation: The Welfare Costs of Natural Gas Vehicles," Resources for the Future Discussion Paper ENR92-01, Washington, D.C.