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Environmental Pricing Policies for Transportation: A Distributional Analysis of the Twin Cities

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As the cost of transporting people increases, questions about paying for the accompanying air and noise pollution increase. This report investigates the distribution impacts of environmental pricing policies on groups in the Twin Cities.

The study uses data on travel behavior in the Twin Cities to examine the distributional impacts of three types of environmental pricing policies: a $.65 optimal downtown, peak period congestion fee; a 10 percent gasoline tax; and a 50 percent transit fare reduction. It evaluates each policy in terms of aggregate welfare costs, revenues, emissions reductions, and cost-effectiveness and looks at distributional impacts by using four groupings--income, region, gender, and age.

The study found that the congestion fee and gasoline tax are regressive, with the burdens of these taxes increasing with income and decreasing as shares of income. The transit subsidy, on the other hand, disproportionately benefits low-income individuals. Other findings show the advantages and disadvantages to urban and suburban commuters and noncommuters and senior citizens.

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Environmental Pricing Policies for Transportation: A Distributional Analysis of the Twin Cities

Final Report

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The research on congestion pricing has been conducted jointly with Jacqueline Geoghegan and Craig Mohn and much of the discussion in this report is based on a joint paper we are preparing. Steve Alderson provided the 1990 Travel Behavior Inventory data, and Mark Filipi and Kevin Roggenbuck graciously provided technical support and emissions estimates for the pricing policies presented here.

Section 2 *(iii)* is based on data from a survey of senior citizens, conducted with funds from the Minnesota Extension Service. Randy Cantrell was a co-P.I. on that project and Catherine Walker administered and conducted the survey.

This project was conducted while I was in residence as a Gilbert White Fellow in the Quality of the Environment Division at Resources for the Future in Washington, D.C. I benefited greatly from conversations and comments from many researchers there, especially Anna Alberini, Winston Harrington and Daniel Sperling.

I would like to thank the Mn/DOT Technical Advisory Panel, chaired by Ronald Cassellius, for their helpful comments and criticisms provided throughout the year. I hope I have adequately responded to them. The panel included Gerald Larson, Jon Bloom, David Braslau, Candace Campbell, Jody Hauer, Scheffer Lang, Perry Plank, Barbara Quade and Bill Smith.

I would also like to thank Professor Herb Mohring for providing comments on an earlier draft report. I, of course, am responsible for any errors remaining in this report.

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Executive Summary

This study uses data on travel behavior in the Twin Cities to examine the distributional impacts of three types of environmental pricing policies: a $0.65 optimal downtown, peak-period congestion fee, a 10% gasoline tax and a 50% transit fare reduction. Each of these policies is evaluated in terms of aggregate welfare costs, revenues, emissions reductions and cost-effectiveness. Distributional impacts are examined using four groupings: income, region, gender and age. The welfare costs used to examine distributional impacts are defined as the expected dollar plus inconvenience costs predicted by the travel behavior model for each of the policies.

It is found that both the congestion fee and gasoline tax are regressive, that is, the absolute burdens of these taxes increase with income, but decrease as shares of income. The congestion fee is particularly regressive for the sample of downtown work commuters. Higher-income individuals are three times more likely to commute to a downtown area during peak hours for work, but lower-income commuters experience cost burdens four times as high in terms of shares of household income. The transit subsidy, on the other hand, disproportionately benefits low-income individuals.

Urban noncommuters (those living in Minneapolis / St. Paul proper) are harder hit by the congestion fee than suburban noncommuters because they are more likely to travel to the downtown areas for nonwork purposes, but suburban residents are harder hit by the gasoline tax than urban residents because they typically drive more miles. Suburban commuters are harder hit than urban commuters because they are more likely to drive alone than carpool or take the bus. The bus subsidy disproportionately benefits urban residents relative to suburban.

Senior citizens bear less burden from the taxes than the rest of the population, primarily because they travel less and have more flexible schedules. As with all "groupings," there are individuals in each of the defined groups that are very hard hit relative to others in the group but

these impacts are diluted by aggregation.

Both the bus subsidy and gasoline tax are found to have relatively small effects on automobile use and carbon monoxide (CO) emissions. The 10% gasoline tax, for example, reduces overall automobile use by 0.16% and emissions of CO by 0.19%, at a welfare cost of $18,732 per ton of CO reduced. The bus subsidy reduces automobile use by 0.46% and CO emissions by 0.53%, for a welfare cost of $1,085,598. The downtown, peak-period congestion fee reduces traffic in the downtowns during peak hours by 9-10%, which translates to a total change of approximately 0.17% in regional automobile use and a CO emissions reduction of 0.22%. Very large price changes appear to be necessary to reduce automobile use and emissions substantially.

1. Introduction: Environmental Policies for Transportation: A Distributional Analysis

The primary purpose of the surface transportation system is to move people, goods and services to and from the places they want to go, or need to be. But because vehicles cause air, water and noise pollution, this purpose seems to be directly at odds with environmental goals. 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. A recent estimate suggests that air and noise pollution costs from automobile use in the Twin Cities metropolitan area total over a quarter of a billion dollars per year in 1990 dollars (Konheim and Ketcham 1993).

The challenge for transportation / environmental policymakers is to design a set of policies that will effectively reduce emissions at the least cost to transportation users. From an economic perspective, the solution is pricing: charging users of the system the *correct* price for the services they are using. The correct price is equal to the marginal cost users impose on the system and society when they drive. But pricing is politically unpopular for several reasons, among them, the expected distributional consequences that transportation taxes might have. Many argue that such taxes would be *regressive*, or, would disproportionately harm the poor.

This report investigates the distributional impacts of environmental pricing policies on groups in the Twin Cities. It is organized as follows: the present chapter reviews economic and equity issues associated with the development of environmental policies for transportation and suggests that pricing policies can be appropriate mechanisms for effectively reducing emissions. Chapter 2 summarizes travel behavior in the Twin Cities using survey data from three sources: the 1990 Public Use Micro

Sample, a product of the U.S. Census (PUMS), the 1990 Twin Cities Travel Behavior Inventory (T.B.I.), and a 1993 survey of senior citizens in the Twin Cities, conducted by the author. Chapter 3 describes three environmental pricing policies: congestion pricing, a gasoline tax and a bus fare subsidy, and their aggregate economic and travel behavioral impacts. Chapter 4 evaluates the three pricing policies with respect to income, region, gender and age. Chapter 5 offers conclusions and recommendations.

The remainder of this chapter discusses *(i)*, the concept of economic efficiency, *(ii)* equity, and *(iii)* potential transportation / environmental policies and their expected economic and equity impacts.

i) Efficiency as a Policy Goal

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 (externality) 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 personal travel time. Externality costs include congestion costs (the increased time spent by others on a congested 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.

Private benefits of automobile use refer to the utility that individuals derive from getting to different destinations. Individuals weigh their own, private costs against the private benefits they anticipate from driving and choose to drive up to the point where the marginal private cost of driving is equal to the marginal private benefit. Drivers do not, however, take account of the externalities they create. In the case of a personal automobile trip, the externality costs are described above: increased congestion, pollution and decreased safety. There are no clear externality benefits associated with a personal automobile trip and therefore, the result is a market inefficiency with total social costs exceeding total benefits.

A basic concept in economics is that the best way to pursue a policy goal is to target that goal directly. Efficient policies accomplish their goal at least-cost. If people paid the full social cost of driving (including congestion and environmental externalities), we would obtain a solution that reduces these externalities by discouraging low-priority automobile trips (Baumol and Oates 1988). This solution would indeed accomplish the goal of reducing externalities at least-cost.

Unfortunately, the full social cost of driving is unknown because it is dependent on so many factors, many of them unmeasurable. In lieu of a full efficiency analysis, we can evaluate the cost-effectiveness of an environmental policy by estimating the dollar cost associated with a unit reduction in emissions. Using the dollar-per-unit metric, policies can be compared to find the least-cost approach for achieving certain environmental objectives. Harrington, Walls and McConnell (1994) summarize the cost-effectiveness of a range of environmental policies for transportation.

ii) Equity as a Policy Goal

The concept of transportation "equity" is, so far, a vague notion. Cameron (1994), suggests that an equity analysis of the transportation system should focus on whether all residents have the mobility services they need. He concedes, however, that this concept is immeasurable, and focuses instead on measuring the distribution of transportation benefits and costs across income groups in Southern California, thus measuring *inequality* in the system, a concept that is he believes is related to, but not the same as, inequity. In an earlier study, Altshuler, Womack and Pucher (1979) measured the levels of transportation services to poor, elderly and handicapped persons. They refer to three possible "equity" concepts: 1) to each according to his or her financial contribution, 2) to each an equal share of public service regardless of financial contribution or 3) to each a share of public service based on need as government has chosen to define it. Both studies conclude that there are inequities in the system with disadvantaged groups receiving fewer net benefits than others.

This study is primarily concerned with the equity impacts of environmental pricing policies. It does not attempt to judge the status quo system. According to a study by the Congressional Budget Office (1992), equity considerations for policies should focus on three concepts: 1) similarly situated individuals should be treated similarly, 2) those with more money should pay higher taxes than those who have less, and 3) people who derive benefits from a service should pay for it.

Any policy is going to result in some individuals being "winners" and some "losers." A gasoline tax, for example, imposes a financial cost on all drivers and inconveniences those who choose to avoid the tax be altering their travel behavior. On the other hand, if the tax reduces automobile use in smoggy areas, it benefits the area's residents by providing cleaner air. Gasoline taxes also generate revenues that can be used to benefit certain individuals or communities.

A well-accepted principle in economics, known as the Hicks-Kaldor criterion, is that a policy should benefit the winners enough so that they would be willing to fully compensate the losers if the policy were enacted. In the gasoline tax example, this implies that the beneficiaries from cleaner air should be willing to pay those who are inconvenienced enough so that they feel compensated for their inconvenience. The revenues generated, if offered back to consumers in some form of tax rebate, can perfectly offset the financial losses associated with the gasoline tax. Unfortunately, it is nearly impossible to implement such a compensation scheme in practice, especially in an example where many people are losers.

Environmental policies are particularly difficult to implement because the benefits associated with cleaner air or water, such as health and aesthetic benefits, are hard to see, and are not necessarily directly linked to the policy in peoples' minds. This can leave environmental policies for transportation with few advocates (people who believe themselves winners) and many adversaries.

In addition to assessing the effects of policies on themselves, people care about fairness. People do not like to see others hit hard by government, especially when they can identify with, or classify, the losers. Taxes on non-luxury items, such as automobile use, are generally assumed to be *regressive* -- that is, they disproportionately burden lower-income households. A regressive tax is one that decreases *as a share of income* as income increases. Under a regressive tax, low-income households pay a higher percentage of their income than higher-income households even though in absolute terms, the higher-income households might pay more. Regressivity is often mentioned as a barrier to the implementation of a gasoline tax increase.

Other groups of interest for political purposes are senior citizens, minorities, women, the disabled and regions. Due to data limitations, this report will focus on the impacts of pricing policies on a subset of these groups: income groups, urban and suburban households, women, and senior citizens (see Appendix D for a list of recommendations about future travel behavior inventories).

iii) Summary of Environmental Policies for Transportation

Table 1.1 summarizes several potential environmental policies for transportation in terms of their efficiency and equity implications. Efficiency is evaluated based on the ability of a policy to effectively target emissions. Equity is evaluated by defining the potential losers associated with a policy.

There is a growing literature evaluating emissions-related policies including 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 fuel vehicles and California emissions standards.

Table 1.1 Potential Environmental Policies for Transportation

Policy target	Potential Policies	Efficiency Potential	Potential Losers
Reducing emissions from new vehicles	- Emissions standards for new vehicles - Alternative fuel vehicles	**LOW** -New cars are not high-emitting vehicles - Might postpone new car purchases	New <u>and</u> used car buyers
Reducing emissions from existing, high-emitting vehicles	- Inspection and Maintenance programs - "Cash for Clunkers" programs	**HIGH** (provided identification and repair - or scrappage - of target cars is efficient)	Owners of high-emitting (generally older) vehicles
Reducing emissions by reducing VMT's	Gasoline tax	**UNCERTAIN** - Depends on emissions per VMT - Doesn't target high emitting vehicles, regions or times	All drivers
Reducing emissions by targeting vehicle use in congested areas or peak hours	- Congestion pricing - Parking pricing	**HIGH** (for particular region targeted)	Commuters and other users of congested roads during peak times
Reduction emissions by encouraging transit use	- Reduce transit fares - Expand transit system - Improve transit amenities	**LOW** Potential for increase in transit use is relatively low	Transit agencies collect less revenues

If we are interested in targeting automobile-related emissions we must design policies that create the appropriate incentives. The cost-effectiveness of an automobile-related program depends crucially on its ability 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 owners of high-emitting vehicles. 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. (1995) has shown that optimal congestion fees can 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 (dollar outlays, time and inconvenience) and the expected benefits (reduced congestion and emissions). The research presented here focuses on how expected travel cost and travel time change individual behavior, and on the relative welfare costs and benefits experienced by different groups of people because of these changes.

2. Travel Behavior in the Twin Cities

This chapter presents summary statistics on travel behavior in the Twin Cities using three survey data sources. The first is the 1990 PUMS (Public Use Micro Sample), which is based on the long form of the 1990 U.S. Census. The data contain information on work commute trips only. The second is the 1990 Travel Behavior Inventory which contains data on all trips taken by all individuals over 5 years of age in approximately 1% of the households in the Twin Cities Metropolitan Area. The third is a survey of senior citizens in the Twin Cities area, conducted by the author with support from the Minnesota Extension Service.

Presenting the results from three different data sets offers several advantages. First, we are able to verify results that are consistent across data sets. Second, each data set has special strengths and weaknesses so that together, they offer much more information than any one data set alone. For example, the analysis of pricing policies that appears in Chapters 3 and 4 is based on the Travel Behavior Inventory, the only data set complete enough to analyse response effects. But this data set does not identify non-white populations. Using the PUMS data set, we can speculate about the impacts of the pricing policies on non-whites even though we cannot explicitly analyse them using the Travel Behavior Inventory. The PUMS data set is of limited use though, because it covers work commutes which are less than 25% of all travel.

i) PUMS Data

Tables 2.1 and 2.2 present mode choices for commute trips in St. Paul and Minneapolis broken down by gender, race and income categories. In both cities, we find that men are more likely than women to commute by automobile, and if so, to commute alone. For example, in St. Paul, 73.5% of men commute alone to work while 62% of women do. The difference between these two figures is predominantly because of different rates of bus use. Walking, biking and carpooling are approximately equal for the two groups.

Differences in commute patterns are more noticeable in the racial categorization. In St. Paul, 70% of whites commute alone while only 52% of non-whites do. Non-whites are more likely to take the bus, carpool, bike or walk than whites are.

The income categorization shows a positive relationship between commuting alone and household income. Bus use and walking or biking tend to decrease as household income rises. There are a couple of glitches in the trends, however. For example, in St. Paul, bus use is 8.6% for individuals from households with income between $75,000 and $100,000. This is most likely because these individuals work in downtown St. Paul or some other destination where the bus is relatively convenient.

The PUMS data also has information on commute distances and times. These statistics (not reported here) are relatively constant over the different categories defined here, indicating, perhaps, that household and work locations are chosen to maintain commute distances and times at reasonable levels.

Table 2.1 Mode Choices for Work Trip - St. Paul (1990 PUMS)

	Male	Female	White	Other
automobile	84.00%	74.40%	80.50%	68.30%
bus	7.40%	13.60%	9.60%	17.80%
walk or bike	6.60%	7.30%	6.40%	11.80%
work at home	1.50%	0.80%	2.90%	1.00%

<u>If automobile then:</u>

	Male	Female	White	Other
alone	87.50%	83.50%	86.50%	76.70%
carpool	12.50%	16.50%	13.50%	23.30%

<u>By income</u>

	< $10,000	$10-20,000	$20-30,000	$30-40,000
automobile	65.40%	78.70%	85.50%	92.80%
bus	13.40%	11.90%	10.10%	4.40%
walk or bike	15.00%	6.00%	3.30%	1.50%
work at home	5.10%	2.40%	0.90%	1.00%

<u>If automobile then:</u>

	< $10,000	$10-20,000	$20-30,000	$30-40,000
alone	81.00%	85.20%	86.40%	89.80%
carpool	19.00%	14.80%	13.60%	10.20%

	$40-50,000	$50-75,000	$75-100,000	> $100,000
automobile	86.50%	94.90%	84.60%	95.30%
bus	7.70%	2.60%	8.60%	0.00%
walk or bike	3.00%	1.70%	2.10%	0.00%
work at home	2.80%	0.80%	4.60%	4.70%

<u>If automobile then:</u>

	$40-50,000	$50-75,000	$75-100,000	> $100,000
alone	90.10%	85.40%	94.90%	91.10%
carpool	9.90%	14.60%	5.10%	8.90%

Table 2.2 Mode Choices for Work Trip - Minneapolis (1990 PUMS)

	Male	Female	White	Other
automobile	72.70%	67.60%	72.40%	58.24%
bus	12.80%	20.10%	14.50%	27.40%
walk or bike	11.20%	7.90%	9.50%	10.60%
work at home	2.70%	3.40%	3.20%	2.30%

<u>If automobile then:</u>

			White	Other
alone			85.30%	75.20%
carpool			14.70%	24.80%

<u>By income</u>

	< $10,000	$10-20,000	$20-30,000	$30-40,000
automobile	55.70%	66.80%	78.90%	84.20%
bus	20.80%	20.90%	13.50%	8.20%
walk or bike	18.20%	9.10%	5.60%	5.50%
work at home	4.40%	2.60%	1.70%	2.00%

<u>If automobile then:</u>

	< $10,000	$10-20,000	$20-30,000	$30-40,000
alone	79.40%	83.00%	84.40%	88.90%
carpool	20.60%	17.00%	15.60%	11.10%

	$40-50,000	$50-75,000	$75-100,000	> $100,000
automobile	86.00%	85.30%	86.80%	83.90%
bus	7.80%	7.50%	6.80%	0.70%
walk or bike	1.40%	1.90%	4.70%	8.50%
work at home	4.20%	4.60%	1.70%	6.90%

<u>If automobile then:</u>

	$40-50,000	$50-75,000	$75-100,000	> $100,000
alone	89.50%	87.60%	83.90%	92.90%
carpool	10.50%	12.40%	16.10%	7.10%

ii) 1990 Travel Behavior Inventory

The 1990 Travel Behavior Inventory for the Twin Cities Metropolitan Area has a sample size of 24,511 individuals in 9,746 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 the day of the survey. The data include mode choice, travel time and individual and household demographic characteristics.

We removed all observations 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, "trips" were redefined because each trip segment does not entail a new, independent mode choice: if an individual leaves home driving a car, subsequent transportation decisions will likely involve the car. We identified two points at which most people 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 on the bus 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.

Some characteristics of trip behavior are presented in Tables 2.3 and 2.4. Table 2.3 shows the average number of trips recorded in the one-day travel diaries by different groups. Note that trips here are defined as round trips and may include several segments. Trip-making increases slightly as income increases although most of this increase appears to be due to work trips. Men take more trips than women but women take more nonwork trips than men. Suburban individuals take more trips than urban. Senior citizens take significantly fewer trips than others; almost half recorded no trips on the day of the survey.

The data in Table 2.4 verify the relationships, noted in the PUMS data, about mode choice by income and gender. Use of the bus decreases as income increases, and women are more likely to take the bus than men. In addition, we find that urban residents are more likely to take the bus than suburban, and senior citizens are *less* likely to take the bus than the rest of the population. This final result seems to defy conventional wisdom and is probably a result of the larger number of trips taken by senior citizens who do not take the bus. The statistics in table 2.4 are averaged over all trips, not individuals.

Higher-income individuals are more likely to travel during peak times and to the downtown areas than lower-income individuals. Urban residents are much more likely to go to one of the downtowns than suburban residents, and senior citizens are less likely to travel during peak times or to the downtown areas.

TABLE 2.3 Trip-Making Behavior Based on One-Day Travel Diaries (1990 T.B.I.)

	Total Number of Trips	Total Number of Nonwork Trips	% Taking Zero Trips
Full Sample	1.97	1.22	15.50%
Income Group 1	1.84	1.24	19.32%
Income Group 2	2.00	1.24	14.50%
Income Group 3	2.07	1.17	12.83%
Women	1.89	1.25	16.54%
Men	2.06	1.18	14.32%
Suburban	2.00	1.23	15.04%
Urban	1.89	1.19	16.76%
Under 65 year of age	2.06	1.23	13.78%
65 years of age and over	1.28	1.00	44.81%

TABLE 2.4 Trip Characteristics (1990 T.B.I.)

	% Trips in auto alone	% Trips in shared auto	% Trips by bus	% Trips during peak times	% Trips to one of the downtowns
Income Group 1	58.54%	38.82%	2.63%	36.73%	3.29
Income Group 2	63.38%	34.49%	2.13%	40.70%	5.51
Income Group 3	72.09%	26.36%	1.55%	45.95%	8.00
Men	58.85%	38.64%	2.51%	41.71%	5.30%
Women	71.02%	27.34%	1.65%	40.57%	5.97%
Suburban	65.97%	32.92%	1.09%	41.17%	4.38%
Urban	61.32%	33.78%	4.90%	41.12%	9.17%
Under 65 year of age	65.55%	32.34%	2.11%	42.28%	5.74%
65 years of age and over	56.87%	41.31%	1.81%	29.83%	4.49%

iii) Senior Citizens' Travel Behavior in the Twin Cities

According to the Travel Behavior Inventory, senior citizens take 38% fewer trips on a typical day than the rest of the population. Altshuler et al. (1979) suggest that there are two primary reasons for the falloff in travel observed with increased age: retirement from the labor force and deteriorating health. If we consider nonwork trips only though, we find that senior citizens take 19% fewer trips than the rest of the population, a smaller, but still noticeable difference. It is important to question whether the decrease in trip-making with age is a function primarily of individual choices or inaccessibility of the transportation system.

To examine this question, the author and co-P.I., Randell Cantrell, undertook a research project sponsored by the Minnesota Extension Service, to survey the travel behavior of senior citizens. The purpose of the survey was to determine whether this population has special problems or concerns associated with this population and their access to transportation. Summary tables of the findings from this survey are presented in tables 2.5-2.12. Free form responses to the final open-ended question of the survey, which asked for additional comments about the transportation system are presented in Appendix A.

Table 2.5: Characteristics of Full Sample - 1993 Survey of Senior Citizens and Transportation (323 observations)

Variable	Summary Statistic
Age	74.19 years
% Male	37.21%
% with driver's license	75.16%
% with access to a car	50.15%

Table 2.6: Trip Characteristics

Go to Grocery store	
# trips per month	6.06 / month
average one-way distance	2.36 miles
average time per one-way trip	8.78 minutes

Visit Family and Friends	
# trips per month	6.44 / month
average one-way distance	12.21 miles
average time per one-way trip	22.35 minutes

Attend Social Functions	
# trips per month	7.35 / month
average one-way distance	5.53 miles
average time per one-way trip	13.08 minutes

Conduct Personal Business	
# trips per month	5.21 / month
average one-way distance	4.25 miles
average time per one-way trip	11.20 minutes

Visit Doctor	
# trips per month	0.93 / month
average one-way distance	5.68 miles
average time per one-way trip	15.64 minutes

Table 2.7 Mode Choices

Go to Grocery Store	% Using Mode	% Satisfied
Drive Self	61.20%	99.45%
Walk	6.02%	100.00%
Take Public Bus	4.01%	91.67%
Ride with Family or Friend	25.10%	92.00%
Private Van, Metro Mobility, Taxicab	3.68%	61.20%
Visit Family or Friends	**% Using Mode**	**% Satisfied**
Drive Self	5.99%	100.00%
Walk	3.11%	100.00%
Take Public Bus	3.11%	88.90%
Ride with Family or Friend	32.20%	97.90%
Private Van, Metro Mobility, Taxicab	1.73%	100.00%
Attend Social Functions	**% Using Mode**	**% Satisfied**
Drive Self	63.40%	100.00%
Walk	3.50%	88.90%
Take Public Bus	3.50%	100.00%
Ride with Family or Friend	25.30%	81.80%
Private Van, Metro Mobility, Taxicab	4.28%	81.80%
Conduct Personal Business	**% Using Mode**	**% Satisfied**
Drive Self	64.50%	98.90%
Walk	4.76%	92.30%
Take Public Bus	7.33%	95.00%
Ride with Family or Friend	21.60%	98.30%
Private Van, Metro Mobility, Taxicab	1.83%	100.00%
Visit Doctor	**% Using Mode**	**% Satisfied**
Drive Self	57.60%	99.10%
Walk	2.53%	100.00%
Take Public Bus	12.63%	88.00%
Ride with Family or Friend	24.30%	93.75%
Private Van, Metro Mobility, Taxicab	3.03%	100.00%

Table 2.8 Characteristics by Age Category

	ages 65-69	ages 70-79	ages 80 +
# of observations	86	128	109
% Male	41.9%	34.4%	36.8%
% With Driver's License	97.7%	75.8%	55.8%
% With Access to Car	57.0%	50.0%	45.0%

Go to Grocery Store	ages 65-69	ages 70-79	ages 80 +
# Trips per month	6.47	6.41	5.29
Average Distance	2.13 miles	1.99 miles	3.05 miles
Average Time	7.87 minutes	8.56 minutes	9.83 minutes

Visit Family and Friends	ages 65-69	ages 70-79	ages 80 +
# Trips per month	8.69	5.96	5.13
Average Distance	9.55 miles	14.9 miles	10.6 miles
Average Time	19.66 minutes	24.88 minutes	21.32 minutes

Attend Social Functions	ages 65-69	ages 70-79	ages 80 +
# Trips per month	9.4	7.36	5.19
Average Distance	5.4 miles	6.2 miles	4.47 miles
Average Time	13.04 minutes	14.68 minutes	10.64 minutes

Conduct Personal Business	ages 65-69	ages 70-79	ages 80 +
# Trips per month	7.9	4.64	3.64
Average Distance	3.87 miles	3.08 miles	6.17 miles
Average Time	11.17 minutes	10.33 minutes	12.31 minutes

Visit Doctor	ages 65-69	ages 70-79	ages 80 +
# Trips per month	0.82	0.99	0.96
Average Distance	5.93 miles	5.64 miles	5.47 miles
Average Time	14.64 minutes	16.26 minutes	15.78 minutes

Table 2.9 Characteristics by Gender

	Male	Female
# of observations	115	194
% With Driver's License	0.948	0.639
% With Access to Car	0.53	0.5

Go to Grocery Store	Male	Female
# Trips per month	5.35	6.48
Average Distance	2.91 miles	2.03 miles
Average Time	8.75 minutes	8.71 minutes

Visit Family and Friends	Male	Female
# Trips per month	6.69	6.38
Average Distance	14.21 miles	10.99 miles
Average Time	23.86 minutes	21.52 minutes

Attend Social Functions	Male	Female
# Trips per month	6.97	7.53
Average Distance	7.07 miles	4.54 miles
Average Time	14.60 minutes	12.22 minutes

Conduct Personal Business	Male	Female
# Trips per month	5.06	5.42
Average Distance	3.81 miles	4.68 miles
Average Time	10.07 minutes	12.28 minutes

Visit Doctor	Male	Female
# Trips per month	0.92	0.97
Average Distance	6.58 miles	5.03 miles
Average Time	15.46 minutes	15.72 minutes

Table 2.10: Mode Use -- Full Sample

Mode	% Using Mode	% Dissatisfied
Drive Self	64.10%	1.24%
Walk	6.50%	0.62%
Take Public Bus	12.70%	0.62%
Ride with Family or Friend	12.40%	1.86%
Private Van, Metro Mobility, Taxicab	33.40%	3.41%

Table 2.11: Mode Use By Gender

	Male		Female	
Mode	% Using Mode	% Dissatisfied	% Using Mode	% Dissatisfied
Drive Self	80.90%	2.61%	56.20%	0.52%
Walk	7.83%	0.00%	5.15%	0.52%
Take Public Bus	11.30%	0.00%	13.90%	1.03%
Ride with Family or Friend	7.83%	4.35%	16.00%	0.52%
Private Van, Metro Mobility, Taxicab	0.20%	2.61%	41.80%	4.12%

Table 2.12: Using Mode By Age Category

Mode	ages 65-69	ages 70-79	ages 80 +
# of observations	86	128	109
Drive Self	86.0%	70.3%	39.4%
Walk	1.2%	4.7%	12.8%
Take Public Bus	10.5%	13.3%	13.8%
Ride with Family or Friend	5.8%	12.5%	17.4%
Private Van, Metro Mobility, Taxicab	15.1%	32.8%	48.6%

Dissatisfied With Mode By Age Category

Mode	65-69	70-74	75-79
Drive Self	1.16%	0.00%	2.75%
Walk	0.0%	0.00%	1.83%
Take Public Bus	1.16%	0.00%	0.92%
Ride with Family or Friend	0.0%	0.00%	5.50%
Private Van, Metro Mobility, Taxicab	3.49%	2.34%	4.59%

Tables 2.5 - 2.7 present summary statistics for the full sample. The average age of the sample is 74 with 37% men. 75% have a driver's license and 50% have access to a car. Table 2.6 shows mode uses for various activities. In general, respondents take trips for a range of purposes, approximately evenly split between personal errands and social activities. The longest trips people make are for visiting family and friends. The most frequent trips are for social activities. Over 60% of the sample drive themselves and 20-25% ride with a friend or family member. The remainder of the sample use alternative modes such as walking, bus or private transportation services.

Table 2.7 presents the satisfaction rates for the various modes used. The ratings are based on a question that asked respondents to rank their satisfaction with the mode they use from 1 to 5. These responses were categorized into two groups. Responses in the range of 3 to 5 (satisfied to very satisfied) were classified as "satisfied." Responses of 1 and 2 (very unsatisfied and unsatisfied) were classified as "unsatisfied."

In general, the ratings are quite high, indicating that for most activities, senior citizens have adequate transportation services. The comments in Appendix A generally corroborate this conclusion. The lowest ratings go to bus for grocery shopping, visiting friends and family, and visiting the doctor; and Metro Mobility and other private services for attending social functions. It should be noted that these lower ratings often occur in the categories where there is a larger than usual sample using the mode. For example, bus receives a satisfaction rating of 88% when 12.6% of the sample take the bus. This indicates that the occasional riders are the most dissatisfied customers. It seems that senior citizens are satisfied with their primary mode choice, but not so satisfied with their occasional, secondary choices. This might indicate a lack of adequate substitute mode choices for senior citizens.

Table 2.8 presents individual and trip characteristics by age group. The percentages of those holding a driver's license and with access to a car each decrease over the age groups defined. In addition, the number of trips tends to decline in each age category. It is not clear whether the increased reliance on public transportation services causes part of the decrease in trip-making, or if the decrease is due to retirement and health reasons. Table 2.9 presents the same statistics for men and women. Women are much less likely to hold a driver's license than men, and they tend to take more trips.

Tables 2.10 and 2.12 present the percentages in the sample who used each mode for any trips and the rates of dissatisfaction. It is interesting to note that Metro Mobility and private services provide at least some service to one-third of the sample. Women are less likely to drive themselves than men are. This is at least partly because fewer of them have driver's licenses, a phenomenon that could change in the future as the current (larger) set of female drivers age. Driving oneself decreases with age, and use of alternatives increase substantially. Dissatisfaction rates are quite low.

Several conclusions can be drawn from these data. Senior citizens of all ages are making trips and are generally satisfied with their mode choices. With age, driving oneself tends to decrease more than trip-making, leading people to use more alternative modes such as public bus, van services and walking. Almost 40% of those 80 years or older, though, continue to drive themselves. The remainder of the population is relatively evenly spread over several transportation options; presumably with each person using that option which best suits his or her lifestyle and needs. The diversity of choices indicates that senior citizens, like most other social or economic groups we tend to define, should not be lumped into one uniform category when evaluating the impacts of transportation policies.

3. Environmental Pricing Policies

From an economic perspective, automobile use is underpriced. Automobile users pay for their gasoline, vehicle wear and tear, road tolls and parking. They also "pay" for their personal travel time in terms of opportunity cost. These costs are known as the private, or user, costs of automobile use. Drivers do not, however, pay for the additional travel time their presence on the roads imposes on others (the congestion externality), and the environmental costs associated with vehicle emissions. These are some of the social costs of automobile use that are not included in the "price."

This underpricing has led to an inefficient outcome: over-reliance on the automobile which has caused substantial traffic congestion and air pollution. The obvious solution to this problem is to correct the price of transportation -- to charge system users for the full cost they impose on the system and society. There are several pricing policies that might be designed for this purpose. This study focuses on three: a congestion pricing scheme, a gasoline tax and a bus subsidy. Each is intended to reduce automobile use: congestion pricing charges automobile users on the most trafficked corridors during the most congested times of day to reduce the congestion externality and the coincident high emissions; a gasoline tax uniformly raises the price of all automobile travel to discourage driving in general; and a bus subsidy increases the *relative* cost of automobile use to discourage driving.

This chapter describes the three pricing scenarios evaluated in this study and their economic impacts, including travel behavior changes, average welfare losses and revenues collected. Chapter 4 addresses the distributional consequences of these pricing policies.

i) A Downtown Peak-period Congestion Fee

The idea of explicitly charging for scarce road space during congested periods was first suggested by Pigou (1920). Recently, the political acceptability of congestion pricing has increased for three reasons: 1) Transportation experts have realized that air pollution and congestion are two related, ubiquitous, and often extreme problems in many urban areas throughout the United States. A recent estimate suggests that emissions under congested conditions can be 250% greater than under noncongested conditions. (CARB 1989). 2) Building more roadway to alleviate congestion is often not an option due to political, financial and air quality constraints. 3) The technology now exists to implement, monitor, and enforce a system of congestion pricing at costs far lower than those of toll booths. A successful test of the technology occurred, for example, in Hong Kong (Catling and Harbord 1985).

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).

This study analyses a congestion fee imposed on all automobiles entering or leaving either the Minneapolis or St. Paul downtown areas during the morning or evening peak hours (defined as 7-9am and 4-6 pm on weekdays). This scheme is similar to the Singapore area licensing scheme (Watson and Holland 1978), and is meant only to address downtown congestion. This type of scheme was chosen because of data and modeling considerations. The data include origin and destination, but not route choice. Since route choice would probably be the first way people would avoid a highway congestion fee, a proper analysis of behavioral response of such a fee is impossible using the data available. (See Mohring and Anderson (1994) for an analysis of optimal per-mile congestion fees on major corridors in the Twin Cities area. See Appendix D for recommendations on variables to collect in future travel behavior inventories).

The econometric travel behavior model used to evaluate the impacts of a congestion fee is presented in Appendix B. The model is designed to estimate demand responses to the congestion fee, including mode, trip timing and destination choice. Because the model is utility-theoretic, we can estimate the welfare impacts individuals experience when the fee is imposed.

Imposition of the congestion fee can have one of three possible effects on people: 1) Some will be "tolled" from the system; that is, some will decide the fee is higher than they are willing to pay for the trip, and they will switch mode, time of day or destination for their trip. In any case, they experience the inconvenience of having to alter their trip plans and so lose personal welfare. 2) Some will pay the fee because the trip is worth at least that much to them. They receive time-savings benefits due to the reduced congestion, but they are still "losers," because the time-savings benefits are not valuable enough to offset the money amount they have to pay to drive. 3) Individuals with a high enough value of time will pay the fee, continue to drive, and experience a welfare gain because the time savings benefits more than offset the money amount they now have to pay.

The model discussed in Appendix B is an equilibrium model that takes account of the fact that reduced congestion will encourage some drivers to get back on the road. The model must be estimated iteratively: given a particular congestion fee, the first-order reductions in congestion and expected travel times are estimated; then the effects are re-calculated using the congestion fee and the new, lower travel time estimates; this dampens the first-order effects and results in less congestion relief and higher travel times than the first-order estimates; this procedure is repeated until an equilibrium is established.

Additional societal benefits associated with congestion pricing are the revenues collected and a reduction in concentrated air pollution due to less start-and-stop driving conditions in congested areas. In this study, the optimal fee is derived by estimating the welfare impacts and revenues associated with a given fee amount, and finding the fee that maximizes total net benefits: revenues plus welfare gains minus welfare losses. The environmental benefits are calculated separately and are considered to be a positive "externality" associated with the fee.

Using the equilibrium model presented in Appendix B, the optimal downtown peak-period congestion fee is found to be $0.65 per automobile. Table 3.1 displays the behavioral results associated with the imposition of this fee. We consider work and nonwork trips separately because work trips are assumed to be more constrained, especially in terms of timing and destination, than nonwork trips. Table 3.2 presents the same results in the form of arc demand elasticities. The elasticity measures the percentage change in the probability of taking the particular trip with respect to a percentage change in the congestion fee. Arc elasticities are measured by taking the changes in demand found in Table 3.1 and comparing those changes with the change in congestion fee. For example, from Table 3.2, a one percent increase in the congestion fee reduces driving alone for work trips by 0.19% and driving alone for nonwork trips by 0.27%. The congestion fee increases both carpooling (slightly) and bus use. The elasticity measures are relatively low, but quite typical of travel demand elasticities. In all cases, it takes a large price increase to change behavior significantly.

Table 3.1: Equilibrium Effects of a $.65 Optimal Congestion Fee of Downtown, Peak Hour Travel

	Work Trips		Nonwork Trips	
Percentage of sample that:	Before Fee	After Fee	Before Fee	After Fee
Drives alone given Peak hour travel and Downtown destination	56.40%	54.75%	45.08%	42.17%
Carpools given Peak hour travel and Downtown destination	28.39%	29.20%	33.38%	34.26%
Takes Bus given Peak hour travel and Downtown destination	15.16%	16.02%	21.52%	23.52%
Travels during Peak hour given Downtown destination	48.93%	48.93% (no change by assumption)	44.87%	41.86%
Goes to a Downtown destination	3.38%	3.38% (no change by assumption)	7.82%	7.43%

Table 3.2: Arc Elasticity Estimates with Respect to $.65 Congestion Fee

Elasticity	Work Trips	Nonwork Trips
Drive Alone (given timing & destination)	-0.19	-0.27
Carpool (given timing & destination)	+0.15	+0.073
Bus (given timing & destination)	+0.38	+0.41
Peak Hour Timing (given destination)		-0.24
Downtown Destination		-0.12

Table 3.3 shows the cumulative effects of these changes on downtown, peak-period traffic and aggregate welfare. Nonwork automobile trips to the downtown area during peak times are reduced by almost 15%. Work trips are reduced only slightly, but the overall reduction is about 9%. Both work and nonwork trip-makers are losers in the aggregate (although there are surely some winners who have high values of time within each group), but when additional revenues are returned as benefits, the net result is a societal welfare gain of $1,803 per day.

Table 3.3: Daily Total Welfare Impacts of $.65 Congestion Fee for Downtown, Peak-periods[1]

	Work Trips	Nonwork Trips	All Trips
Change in # Vehicles Downtown During Peak Hours	-1.81%	-14.59%	-9.27%
Total Revenues Per Day (TR)[2]	$9,098	$16,514	$25,612
User Welfare Change (UWC)	($7,131)	($16,678)	($23,809)
Total Welfare Benefit Per Day (TR +UWC)	$1,967	($164.00)	$1,803
Sample Size[3]	204	10,706	10,910

[1] Negative values are in parentheses.
[2] These aggregates are based on the sample results inflated by a factor of 100, the survey multiplier.
[3] The sample size for work trips is equal to the number of work tripsin the sample that go downtown during peak hours. Note that only 3% of all trips go to the downtown areas.

ii) A 10% Gasoline Tax

A 10% gasoline tax is intended to reduce the difference between the perceived, personal cost of driving and the social cost. Travelers can avoid the higher cost by switching modes or driving less. Either choice imposes an inconvenience on the traveler and causes a welfare loss. Those who pay the tax and continue driving experience a welfare loss equal to the amount of tax they pay. The tax revenues are a societal benefit. It is assumed in this scenario that the reduction in traffic is diffuse and will not noticeably reduce congestion enough to cause time savings benefits.

Tables 3.4 and 3.5 present the demand responses to a gas tax: the elasticities, again, are relatively low. The nonwork trip-making elasticity is -.053 which means that a 100% price increase would cause a 5.3% decrease in trips. Table 3.6 present the welfare impacts of a gasoline tax. Revenues are substantial: over $100,000 per day, but welfare losses are even greater. This is to be expected since the taxes paid plus the welfare losses experienced by the switchers must exceed the tax revenues. Overall automobile use is reduced by 0.16%.

The reason for the lower responsiveness and higher revenues in the gasoline tax example is that the gasoline tax is a relatively small increase in the price of all trips. Individuals do not react with dramatic behavior changes to this small increase, and aggregate tax revenues are large. The congestion fee is a larger price increase, but only on a certain type of trip. Individuals have more of an incentive, and more ways, to change behavior to avoid the tax.

Table 3.4: Mode Choice Impacts of Gasoline Tax and Bus Fare Reduction

10 %Gasoline Tax

	Work Trips		Nonwork Trips	
Probability	Before Tax	After Tax	Before Tax	After Tax
Drive Alone	77.61%	77.51%	59.41%	59.12%
Carpool	18.93%	19.03%	38.54%	38.79%
Bus	3.43%	3.47%	2.03%	2.05%

50% Bus Fare Reduction

	Work Trips		Nonwork Trips	
Probability	Before	After	Before	After
Drive Alone	77.61%	77.22%	59.41%	59.22%
Carpool	18.93%	18.74%	38.54%	38.28%
Bus	3.43%	4.07%	2.03%	2.53%

Table 3.5 Arc Elasticity Estimates with respect to Gasoline Tax, Twin Cities, 1990

	Work Trips	Nonwork Trips
Drive Alone (Given Timing and Destination)	-.019	-.056
Carpool (Given Timing and Destination)	+.056	+.075
Bus (Given Timing and Destination)	+.12	+.16
Number of Nonwork Trips		-.053

Table 3.6: Daily Welfare Changes From Gasoline Tax and Bus Fare Reduction[1]

	10 % Gasoline Tax	50% Bus Fare Reduction
Change in Revenues	$111,123.00	($76,903.00)
Total Welfare Change	($111,298.00)	$48,618.00
Net Change	($175.00)	($28,285.00)

[1] Negative values are in parentheses.

iii) A 50% Reduction in Bus Fares

A 50% reduction in bus fares is intended to increase the cost of driving *relative* to the cost of using bus. In addition to encouraging mode switches to bus use, the subsidy encourages bus-users to take more trips. An advantage of the subsidy is that it does not carry the political baggage that a gasoline tax does. This does not necessarily mean a large bus subsidy would be politically easy to implement. The lost bus revenues would have to be funded by the public sector, and the public does not typically support increased bus funding. But, as shown in tables 3.4 and 3.5, even a large bus fare reduction has modest impacts on travel behavior: automobile use is reduced by 0.46%. Most importantly, Table 3.6 shows the net welfare loss associated with the subsidy. Although the subsidy produces a large welfare gain, bus revenues decrease by 38.5%, a loss that is not nearly made up by the welfare gains.

iv) Environmental Benefits from Pricing Policies

Environmental benefits associated with the three pricing scenarios are presented in Table 3.7. The traffic and air quality impacts were evaluated by staff at the Metropolital Council using its TRANPLAN regional travel model. Using the traffic changes predicted by the travel behavior model, TRANPLAN generates trip tables and loaded networks which are then run through the regional emissions model, EMIS, to estimate the reduction in carbon monoxide emissions. Details on how TRANPLAN and EMIS are used to evaluate the policy scenarios are provided in Appendix C.

Table 3.7 Impact of Pricing Policies on Carbon Monoxide Emissions

1990				
	Base 1990	\$.65 Downtown, Peak hour Congestion Fee	10% Gasoline Tax	50% Bus Fare Reduction
CO (tons)	1797.95	1794.05	1794.54	1788.44
Change		-3.9	-3.41	-9.51
% Change		-0.22%	-0.19%	-0.53%
2000				
	Build 2000	\$.65 Downtown, Peak hour Congestion Fee	10% Gasoline Tax	50% Bus Fare Reduction
CO (tons)	821.69	819.43	819.8	916.58
Change		-2.26	-1.89	-5.11
% Change		-0.28%	-0.23%	-0.62%

For all three pricing scenarios, reductions in emissions of CO are below 1%. The greatest emissions reductions are obtained by the 50% reduction in the bus fare. It is interesting to note that according to TRANPLAN, both the congestion fee and the gasoline tax reduce total automobile use by about 0.17%. But because the congestion fee is focused on peak hour trips to congested downtown areas (where automobile use is reduced by about 9%), the emissions reduction is greater than for the gasoline tax.

The projected emissions for the year 2000 are based on a greater number of projected vehicle trips but also greater use of cleaner burning fuels and a newer automobile fleet. So total CO emissions are projected to be lower than in 1990. The total CO reductions in the year 2000 are less than in 1990, but the percentage decrease is greater. It should be noted that the behavioral changes predicted by the travel behavior model are short-run estimates that assume work and home location and automobile ownership fixed. By the year 2000, if pricing policies were enacted, these long-run patterns might change, causing greater reductions in automobile use than assumed here. Emissions reductions would then be greater than those in Table 3.7.

Table 3.8 shows the cost-effectiveness of the gasoline tax and bus fare reduction policies in terms of their ability to reduce CO emissions. Cost-effectiveness is derived by dividing the dollar welfare costs associated with each policy by the amount of CO reductions they generate. The gasoline tax reduces CO at a cost of $18,732 per ton and the bus fare reduction reduces CO at a cost of $1,085,598 per ton. We cannot estimate a cost-effectiveness for the congestion fee policy because it generates positive net benefits already. The CO reduction occurs as an additional benefit to the policy and in a sense is a win-win policy in terms of aggregate net benefits.

Table 3.8: Cost-Effectiveness of Gasoline Tax and Bus Fare Reduction

Cost-effectiveness	$.65 Downtown Peak Period Congestion Fee	10% Gasoline Tax	50% Bus Fare Reduction
Net Welfare Impact	+$1,803	-$175	-$28,285
1990 CO Emissions Reduced in tons	3.9	3.41	9.51
Cost per ton of CO reduced	--	$18,732	$1,085,598

4. Distributional Impacts of Pricing Policies

This chapter evaluates the pricing policies presented in the previous chapter in terms of their distributional implications. Four categorizations are considered: income groups, urban and suburban households, men and women, and senior citizens.

i) Income Groups

Income groups are defined by dividing the sample into three, approximately equal-sized groups according to household income *per adult*. No adjustment is made for life-cycle situations, such as student or retiree status. In other words, there are observations in the lower-income group that we might not consider truly poor, but that recorded low household incomes in 1990. This is a standard problem with survey data. The individual welfare costs associated with the pricing policies are presented in Table 4.1 These welfare costs represent the fee payments plus any inconvenience costs associated with switching travel plans less any time savings benefits travelers experience. The congestion fee welfare impacts are divided into work and nonwork trip categories because the assumptions in the congestion pricing model allow work trips less flexibility to avoid the fee.

Table 4.1 shows that welfare costs increase over income groups both for work and nonwork categories. The annual work trip costs are especially high because these trips are typically taken daily. On the other hand, nonwork trips are taken occasionally and are spread over a larger population. Although commuters experience time savings benefits, they are still the largest losers when a congestion fee is imposed on their commutes.

Table 4.1: Annual Individual Welfare Cost (Benefit) of Pricing Policies by Income Group

Household Income Per Capita	% of Sample	Congestion Fee Work Trips	Congestion Fee Nonwork Trips	Gasoline Tax	Bus Fare Reduction
Less than $12,500	31.29%	$91.61	$4.05	$37.78	($24.74)
$12,500 - $20,000	38.41%	$105.71	$5.51	$46.06	($19.97)
Greater than $20,000	30.30%	$128.93	$9.89	$54.97	($15.71)

Annual Individual Welfare Cost (Benefit) <u>as Percentage of Per Adult Household Income</u>

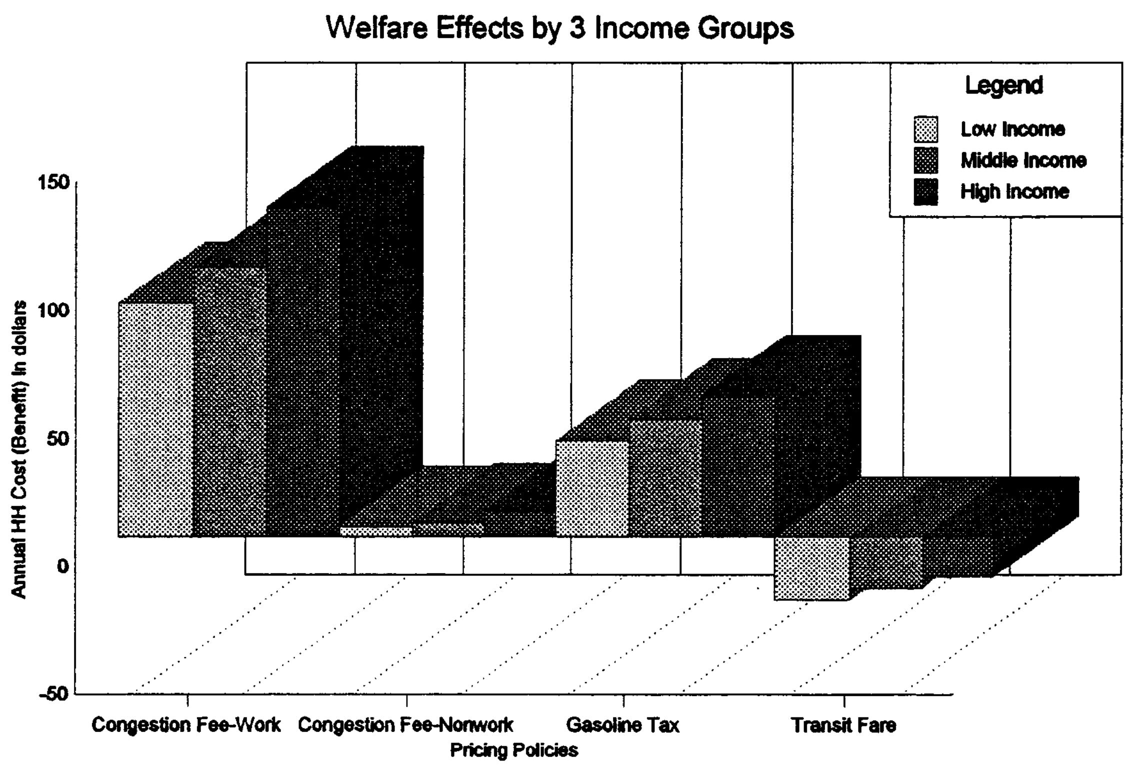
Household Income Per Capita	% of Sample	Congestion Fee Work Trips	Congestion Fee Nonwork Trips	Gasoline Tax	Bus Fare Reduction
Less than $12,500	31.29%	1.55%	0.05%	0.51%	(0.40)%
$12,500 - $20,000	38.41%	0.63%	0.03%	0.28%	(0.12)%
Greater than $20,000	30.30%	0.41%	0.03%	0.19%	(0.05)%

Table 4.1 also shows the welfare costs as percentages of per adult household income. These results show that congestion fees would be very regressive with respect to commuters. Low-income commuters would experience welfare costs over 1.5% of their per adult household income. It should be noted though, that low-income commuters make up only 17% of the sample of downtown peak hour commuters. 57% of commuters are in the high-income category. This lessens the *average* impact over all low-income households. But this would be an unfair statistic to report. Particular individuals in the low-income category will be hit quite hard if a congestion fee is imposed.

A gasoline tax is also found to be regressive, costing the average low-income household 0.5% of their per adult household income. (Krupnick, Walls and Hood (1993) also find that gasoline taxes are regressive). The bus fare reduction, on the other hand, provides relatively more benefits to the low-income group, due presumably, to the higher bus ridership in this category. The benefits are rather low, however.

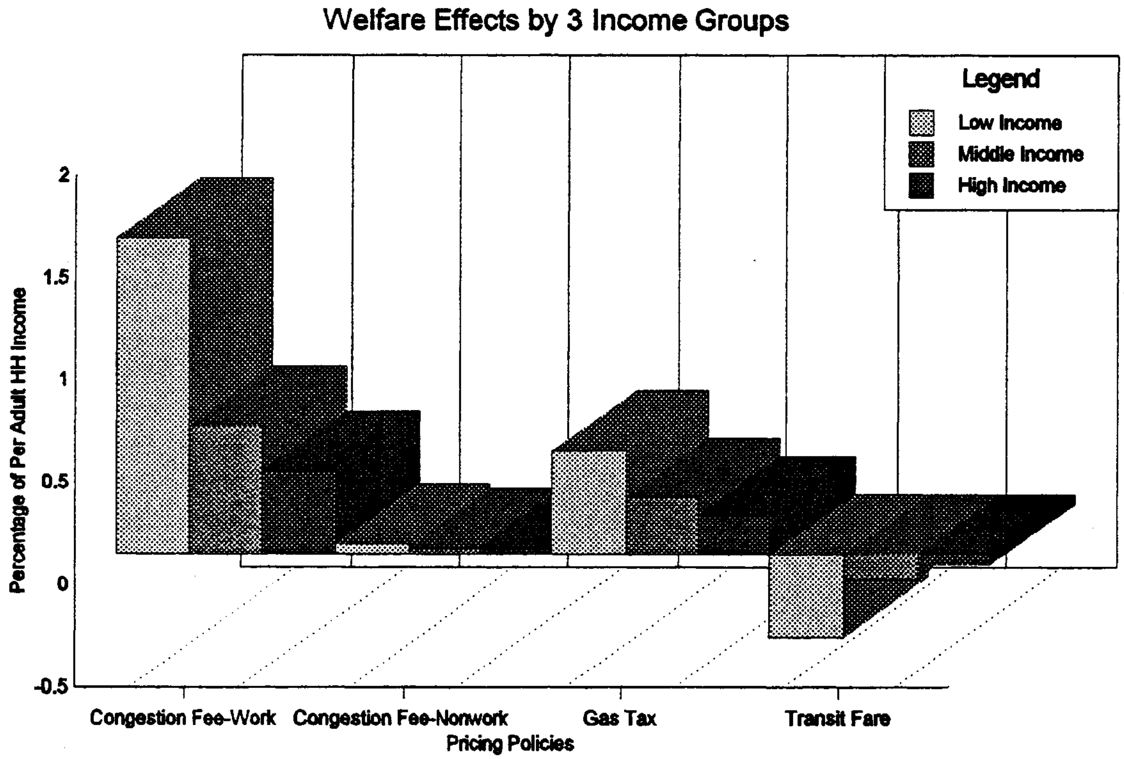
Graphs 4.1 and 4.2 show pictorially the welfare costs and benefits found in Table 4.1. Benefits are shown as negative costs.

Figure 4.1



Welfare Effects by 3 Income Groups
Legend
Low Income
Middle Income
High Income
150
100
50
0
-50
Annual HH Cost (Benefit) in dollars
Congestion Fee-Work
Congestion Fee-Nonwork
Gasoline Tax
Transit Fare
Pricing Policies

Figure 4.2



Welfare Effects by 3 Income Groups
Legend
Low Income
Middle Income
High Income
2
1.5
1
0.5
0
-0.5
Percentage of Per Adult HH Income
Congestion Fee-Work
Congestion Fee-Nonwork
Gas Tax
Transit Fare
Pricing Policies

ii) Urban / Suburban Households

Urban households are defined as those in Minneapolis and St. Paul proper. Suburban travelers are less likely to go to one of the downtowns for nonwork purposes, and are less likely to take the bus than urban travelers. They are also likely to drive more miles. The results in Table 4.2 fit these facts. Suburban commuters experience higher welfare costs from the congestion fee than urban commuters, due primarily to their higher likelihood of driving alone to work. On the other hand, they experience lower costs for nonwork trips because they are less likely to go downtown and can more easily substitute away from the destination. The gasoline tax hits suburban residents harder than urban residents because suburban residents drive more. Suburban residents are hit harder both in terms of absolute costs and costs as a share of per adult household income. Krupnick, Walls and Hood (1993) also find that gasoline taxes hit suburban households (nationally) harder than urban in absolute cost terms, but they find that as a share of income, urban households are harder hit. The bus subsidy primarily benefits urban residents who are much more likely to take the bus already, or be inclined to.

Graphs 4.3 and 4.4 show pictorially the welfare costs and benefits found in Table 4.2. Benefits are shown as negative costs.

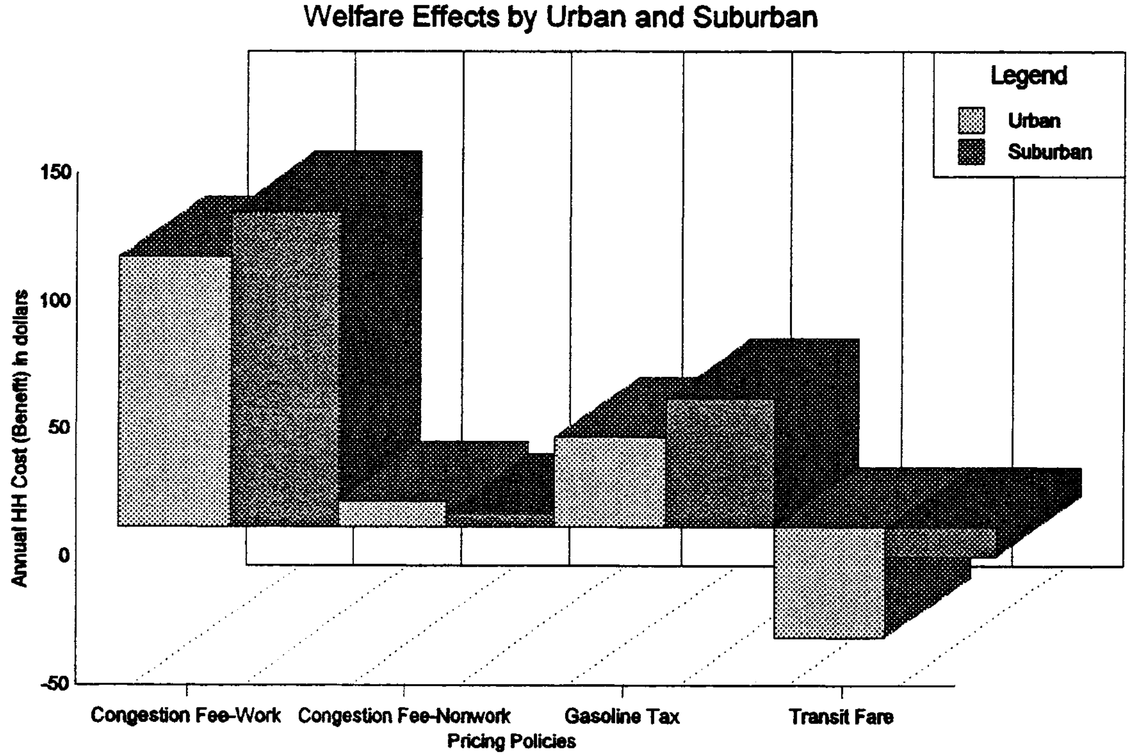
Table 4.2: Annual Individual Welfare Cost (Benefit) of Pricing Policies by Urban/Suburban

Regional Group	% of Sample	Congestion Fee Work Trips	Congestion Fee Nonwork Trips	Gasoline Tax	Bus Fare Reduction
Urban	26.79%	$105.97	$10.07	$35.08	($43.43)
Suburban	73.21%	$123.45	$5.12	$50.22	($11.64)

Annual Individual Welfare Cost (Benefit) as Percentage of Per Adult Household Income

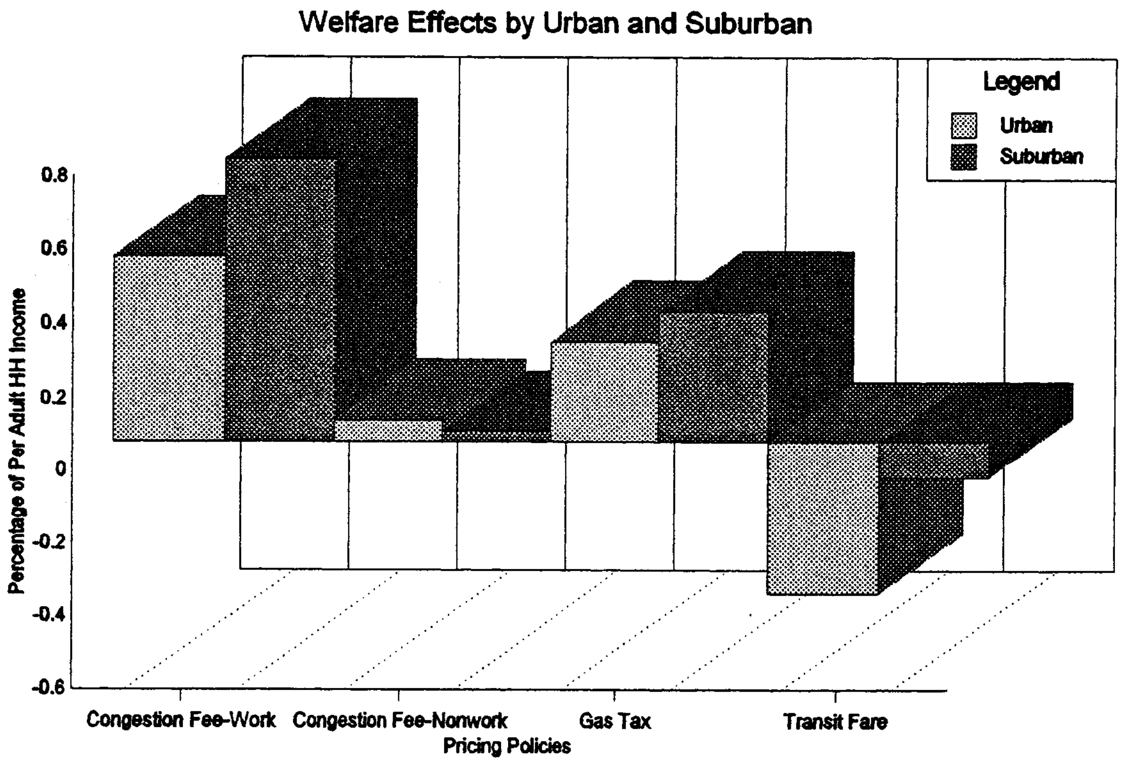
	Congestion Fee Work Trips	Congestion Fee Nonwork Trips	Gasoline Tax	Bus Fare Reduction
Urban	0.50%	0.06%	0.27%	(0.42)%
Suburban	0.77%	0.03%	0.35%	(0.10)%

Figure 4.3



Welfare Effects by Urban and Suburban
Legend
Urban
Suburban
150
100
50
0
-50
Annual HH Cost (Benefit) in dollars
Congestion Fee-Work
Congestion Fee-Nonwork
Gasoline Tax
Transit Fare
Pricing Policies

Figure 4.4



Welfare Effects by Urban and Suburban
Legend
Urban
Suburban
0.8
0.6
0.4
0.2
0
-0.2
-0.4
-0.6
Percentage of Per Adult HH Income
Congestion Fee-Work
Congestion Fee-Nonwork
Gas Tax
Transit Fare
Pricing Policies

iii) Men and Women

The results for men and women are presented in Table 4.3. Men tend to travel more than women and to take the bus less. Although both groups are equally likely to travel downtown during peak times, men experience higher welfare costs because of their greater reliance on driving alone and less inclination to switch modes. Men also experience higher costs from a gasoline tax. The bus fare reduction benefits women more than men.

Graphs 4.5 and 4.6 show pictorially the welfare costs and benefits found in Table 4.3. Benefits are shown as negative costs.

Table 4.3: Annual Individual Welfare Cost (Benefit) of Pricing Policies by Gender

Gender	% of Sample	Congestion Fee Work Trips	Congestion Fee Nonwork Trips	Gasoline Tax	Bus Fare Reduction
Men	46.75%	$131.15	$7.02	$53.98	($16.86)
Women	53.25%	$101.40	$5.87	$39.31	($23.08)

Annual Individual Welfare Cost (Benefit) <u>as Percentage of Per Adult Household Income</u>

	Congestion Fee Work Trips	Congestion Fee Nonwork Trips	Gasoline Tax	Bus Fare Reduction
Men	0.62%	0.04%	0.38%	(0.15)%
Women	0.71%	0.04%	0.28%	(0.22)%

Figure 4.5

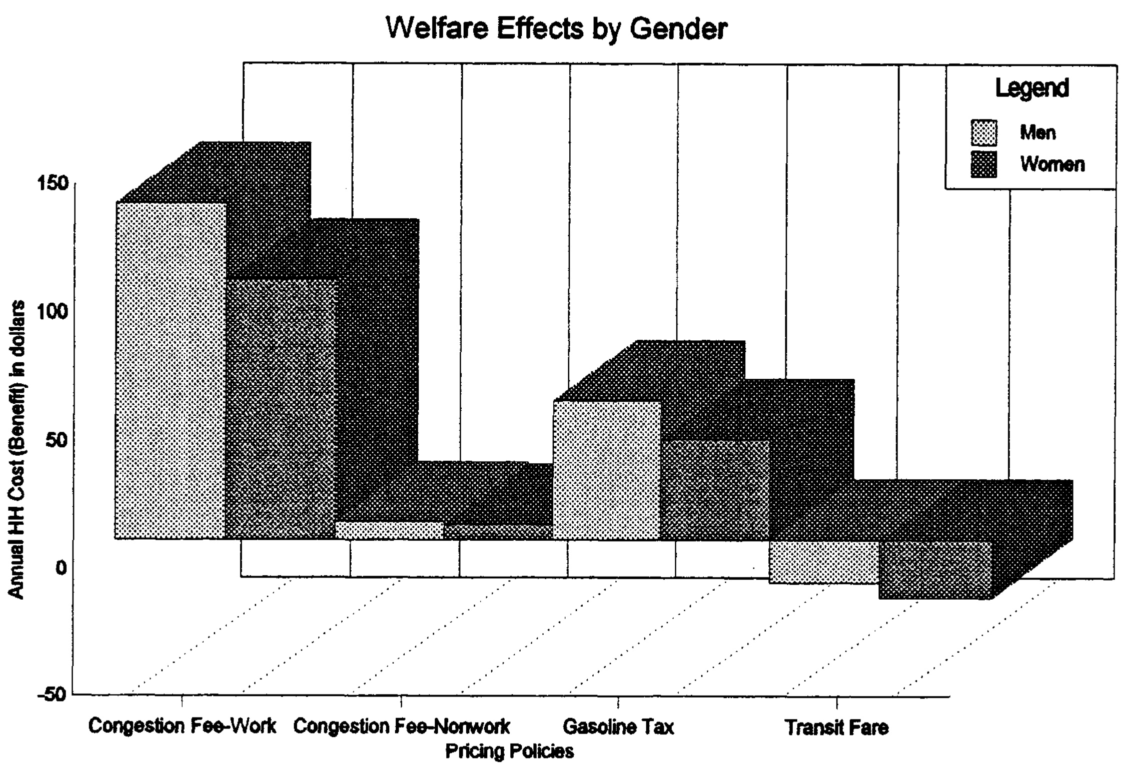
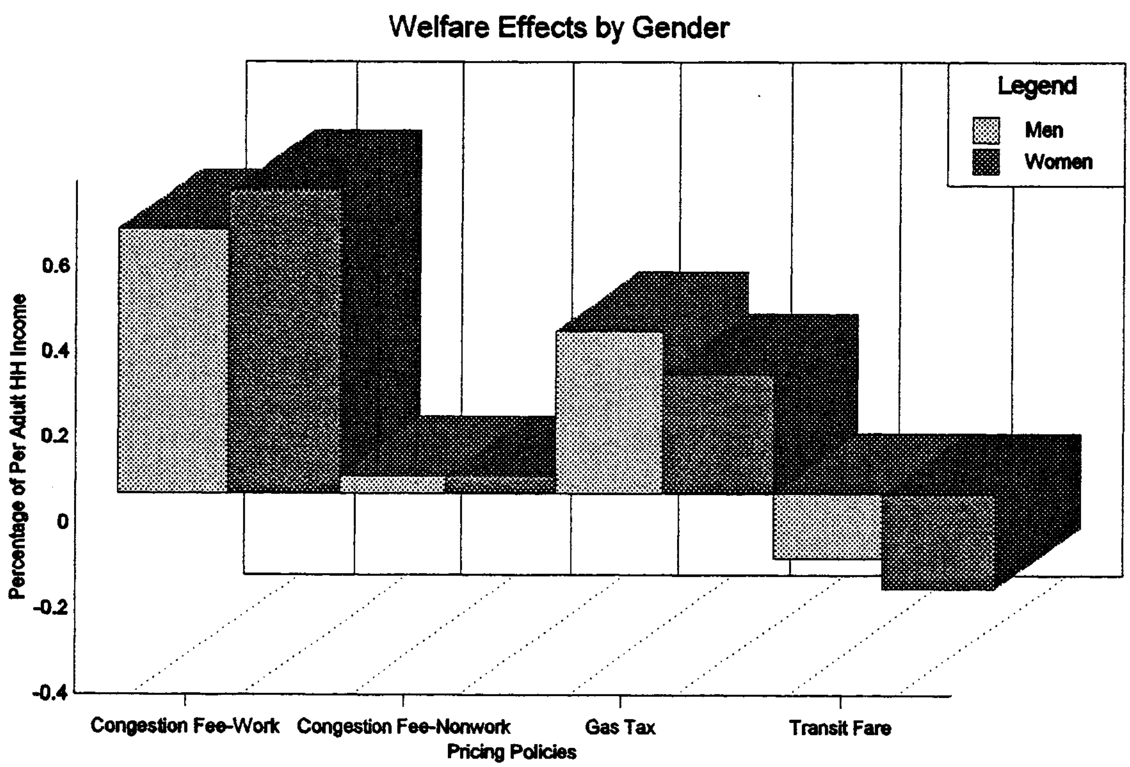

Welfare Effects by Gender
Legend
Men
Women
150
100
50
0
-50
Annual HH Cost (Benefit) in dollars
Congestion Fee-Work
Congestion Fee-Nonwork
Gasoline Tax
Transit Fare
Pricing Policies

Figure 4.6



Welfare Effects by Gender
Legend
Men
Women
0.6
0.4
0.2
0
-0.2
-0.4
Percentage of Per Adult HH Income
Congestion Fee-Work
Congestion Fee-Nonwork
Gas Tax
Transit Fare
Pricing Policies

iv) Senior Citizens

The results for senior citizens are presented in Table 4.4 Senior citizens are defined as those 65 year of age or older. They tend to travel less than the rest of the population and are therefore less negatively impacted by the congestion fee or gasoline tax. If we look at their costs relative to income, we find, however, that the gap between the two groups lessens due to the lower average incomes of senior citizens.

Graphs 4.7 and 4.8 show pictorially the welfare costs and benefits found in Table 4.4. Benefits are shown as negative costs.

Table 4.4: Annual Individual Welfare Cost (Benefit) of Pricing Policies by Age Group

Age Group	% of Sample	Congestion Fee Work Trips	Congestion Fee Nonwork Trips	Gasoline Tax	Bus Fare Reduction
64 and under	87.68%	$115.26	$6.76	$49.06	($22.23)
65 and over	12.32%	insufficient sample size	$3.68	$25.77	($5.65)

Annual Individual Welfare Cost (Benefit) <u>as Percentage of Per Adult Household Income</u>

Age	Congestion Fee Work Trips	Congestion Fee Nonwork Trips	Gasoline Tax	Bus Fare Reduction
64 and under	0.66%	0.04%	0.34%	(0.21)%
65 and over	insufficient sample size	0.03%	0.22%	(0.06)%

Figure 4.7

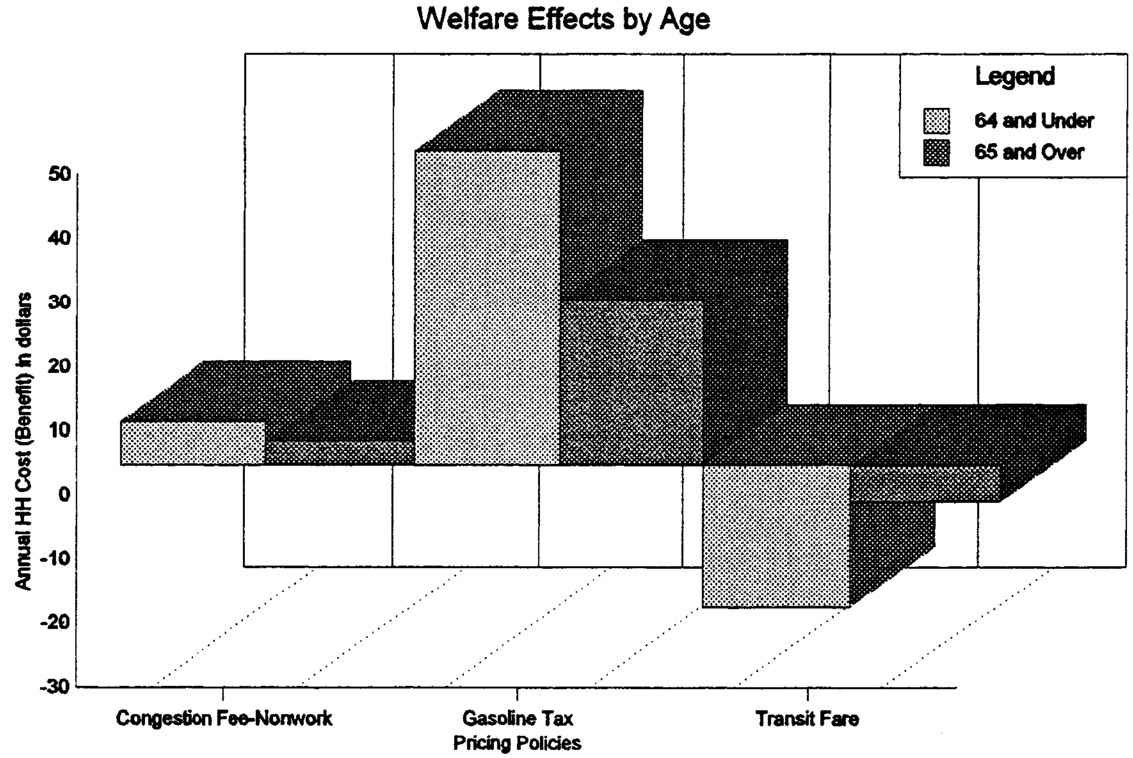
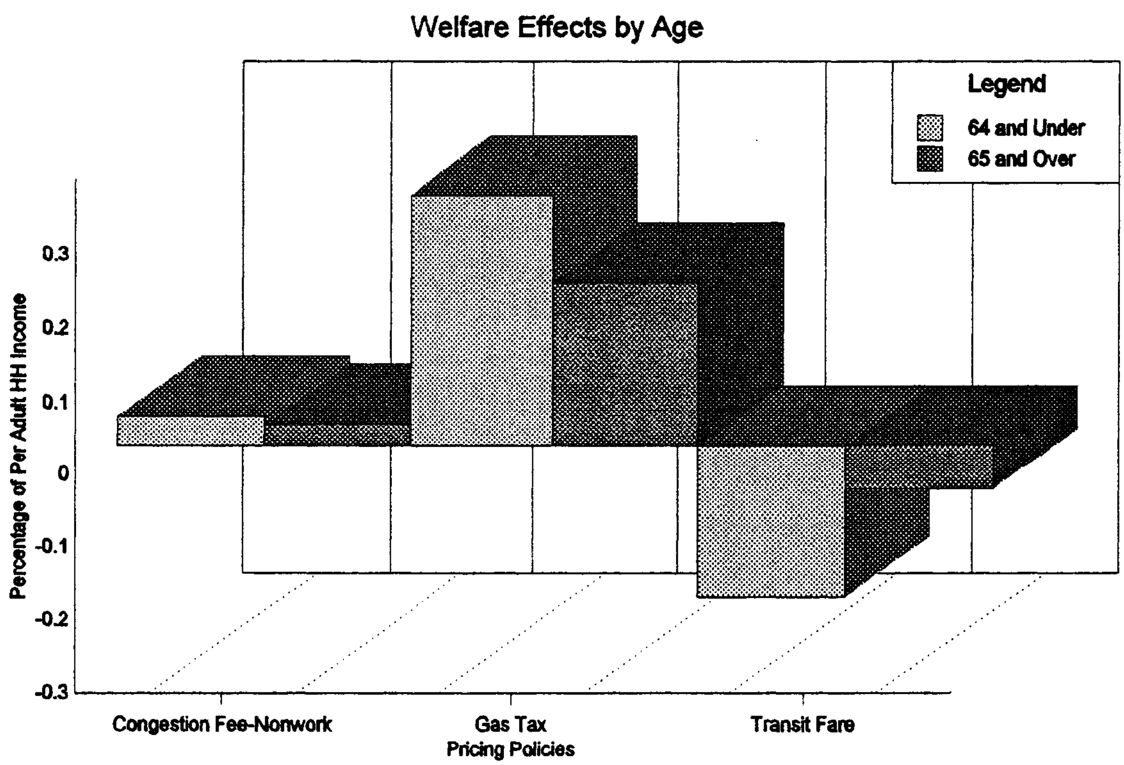

Welfare Effects by Age
Legend
64 and Under
65 and Over
Annual HH Cost (Benefit) in dollars
50
40
30
20
10
0
-10
-20
-30
Congestion Fee-Nonwork
Gasoline Tax
Transit Fare
Pricing Policies

Figure 4.8


Welfare Effects by Age
Legend
64 and Under
65 and Over
Percentage of Per Adult HH Income
0.3
0.2
0.1
0
-0.1
-0.2
-0.3
Congestion Fee-Nonwork
Gas Tax
Transit Fare
Pricing Policies

5. Conclusions

This study has used several travel behavior data sets from the Twin Cities to evaluate the distributional impacts of environmental pricing policies. Specific conclusions are:

- The environmental tax policies examined in this study, a downtown, peak-period congestion fee and a gasoline tax, are regressive. Low-income households would pay a larger share of their per-adult household income than higher-income households if either of these policies were enacted. The gap is especially large between low- and high-income downtown commuters who have little flexibility for avoiding the fees. A bus fare subsidy, on the other hand, benefits lower-income households more than higher-income households.

- Bus fare subsidies benefit urban households substantially more than suburban households due to the higher incidence of ridership among urban households and the higher likelihood of urban residents switching to bus if the lower fares were enacted.

- For nonwork trips, a downtown, peak-period congestion fee would cost urban households substantially more than suburban households because urban residents are more likely to want to travel to the downtown areas.

- Senior citizens are less affected by the congestion fee and gasoline tax than the general population because they travel less and are more likely to use alternative modes.

- As with all "groups" defined, there will be individuals bearing disproportionate costs relative to others in the "group."

- Although we are unable to examine the impacts of pricing policies on minorities explicitly, due to data limitations, the PUMS data suggest that non-whites are more likely to share rides and take the bus than the rest of the population. If their travel patterns are similar to the rest of the population, this indicates that they, as a group, might be less affected by a gasoline tax than others and would benefit more from a bus fare reduction, all other things, including income, being equal. Since the data provide no information on travel destinations and times of day, we are unable to use it to evaluate the effects of a congestion fee. Of course, other characteristics, such as income level and geographic region might offset these effects.

- Price changes must be quite high in order to get a significant reduction in automobile use. The 10% gasoline tax, for example, reduces overall automobile use by only 0.16%. The downtown, peak-period congestion fee is more successful in reducing automobile use. A $0.65 fee reduces use in the downtown areas during peak times by about 10%, an amount that might have a significant impact on congestion levels in these areas. The higher responsiveness to the congestion fee is due to its greater magnitude and the greater number of ways to avoid the fee (by changing mode, timing or destination).

- Both the gasoline tax and congestion fee collect large amounts of revenues that can be used as tax rebates. In order for the policies to work properly as disincentives to drive, such rebates could not be directly linked to the amount of driving households do. One option is for the rebates to be inversely linked to household income to reduce the regressivity of the policy. Rebates would be essential components of any policy package that includes transportation pricing because of the large welfare burdens they impose on all households.

- The gasoline tax is more cost-effective than the bus subsidy in terms of reducing carbon monoxide emissions. The congestion fee has positive net welfare benefits even without the carbon monoxide reductions and reduces carbon monoxide emissions slightly more than the gasoline tax.

- The congestion pricing scheme in this report is a downtown, peak-period fee, not a road-use fee. Distributional results might vary for other type of congestion pricing schemes.

REFERENCES

Adams, J.S. and E.K. Wyly, 1993, *Commuter Linkages Among Counties in the Twin Cities and Greater Minnesota*, Final Report, MN/RC-94/02, Minnesota Department of Transportation, St. Paul.

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.

Altshuler, A., J. Womack and J. Pucher, 1979, "Equity in Urban Transportation," Final Report to U.S. Department of Transportation, DOT/RSPA/DPB-50/79/9, December.

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.

Brownstone, D. and K.A. Small, 1989, "Efficient Estimation of Nested Logit Models," *Journal of Business and Economic Statistics*, 7:1, 67-74.

California Air Resources Board, 1989, "The Air Pollution Transportation Linkage," Sacramento.

Cameron, M.W., 1994, "*Efficiency and Fairness on the Road: Strategies for Unsnarling Traffic in Southern California*, Environmental Defense Fund, Oakland.

Catling, I. and B.J. Harbord, 1989, "Electronic Road Pricing in Hong Kong - The Technology," *Traffic Engineering and Control*, December.

Congressional Budget Office, 1992, *Paying for Highways, Airways, and Waterways: How Can Users Be Charged?*, Washington, D.C., May.

Geoghegan, J.A., B.J. Kanninen and C. Mohn, 1995, "Environmental Congestion Pricing: an Empirical Assessment," unpublished manuscript, University of Maryland, College Park.

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., 1995, "Estimating Mode Choice and Trip Frequency Decisions Using Travel Diary Data," paper presented at the 1995 ASSA meetings, Washington, D.C.

Konheim & Ketcham, 1993, mimeo, Brooklyn.

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.

Meghir, C. and J.-M. Robin, 1992, "Frequency of Purchase and the Estimation of Demand Systems," *Journal of Econometrics*, 53, 53-85.

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.

Pigou, A.C., 1920, *The Economics of Welfare,* Macmillan and Co., London.

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.

Watson, P.L. and E.P. Holland, 1978, *Relieving Traffic Congestion: The Singapore Area License Scheme,* SWP 281, The World Bank, Washington, D.C.

APPENDIX A.

Responses to Survey of Senior Citizens, 1993

Question: Do you have any other comments regarding transportation you would like to share with me?

APPENDIX A. Responses to Survey of Senior Citizens, 1993

Question: Do you have any other comments regarding transportation you would like to share with me?

Glad to have bus if need it.

Take car everywhere and happy with it.

Would like to see Mpls #8 run more often on Sunday - it's difficult to get to church. Walking is not safe in the area. Good bus access. Thankful it is available.

Good service over the years. Available when need it. $.25 is nice. Don't use often because don't go many places.

Retired, so go south in winter, but have good bus service if need it.

4 Blocks to bus - bus only goes downtown. Public bus is not good, need more service.

Difficult to get to doctor because my kids work and they drive me. Bus service not going where need it - only to downtown St. Paul.

No MTC bus service, but not having problems now.

If they take my car away from me, they might as well kill me. I have arthritis and I can't walk too much, but with my car, I can do what I need to do.

As long as I can drive, I guess I don't think too much about it. But it's nice for other people I guess.

MTC should not raise the fares for the elderly. I might have to use it one of these days and on a fixed income it's hard to handle increases.

We would have easy access to public transportation if we wanted to, but there's been no need to so far.

The $.25 deal for seniors on the bus is great. It gets us out of our houses and it's very affordable.

If we are to maintain the quality of life in this area, we must have better public transportation such as light rail. The environment and the economy are going to suffer if we continue to rely on automobiles.

I could take the city bus sometimes, but I just like to travel with somebody else.

We need a rapid bus system and we need to encourage using bicycles. We should raise the gas tax if more revenue is needed for transportation.

I like the park-and-ride systems so you can ride a bus downtown and not have to pay to park downtown. But it's important that the buses run very regularly.

I think this light rail would be a good idea; it would get a lot of cars off the street.

People like their automobiles and aren't too used to using public transportation. They want to go when they want to go and they don't want to wait - it might work on heavily traveled arterial streets, but most people in the suburbs don't want to use it.

I wish there were some service for people to get home from the hospital after out-patient surgery. They won't let you take a bus or a cab, so you have to have a friend take time off from work or something.

Transportation is so important in the modern world that it should be available to anyone at anytime. If I were working outside the house, downtown or something, I'd want a reliable bus service to use.

We get very good bus service here.

I use the bus occasionally to go to downtown St. Paul shopping and I find it very handy.

I don't use public transportation often, so I couldn't say too much about it.

I come from a large family and we have a lot of kids so I can always get where I need to go.

Haven't really used but I have friends who rely on it.

There will come a time when I need public transportation and I will be very interested.

I know it is available but I have a need to know it is there.

Classic questions by people who don't know what to ask elderly. 65 and over is not elderly. This doesn't apply to me. I would be happy to talk to whoever wrote this to give them suggestions.

Public bus should be strengthened. Investigate light rail. Unhappy street cars taken out - less pollution.

I don't use public transportation - it's only for working downtown.

Taking the bus - if I had to - is no problem.

I am within 5 blocks of city bus. I think we have good transportation. I would use public transportation to go downtown.

Good out here.

It's fine.

I don't have any other transportation.

Close to bus line. Prefer to drive.

Now that husband is retired, the car is available. Likes that the bus is available.

Gas without ethanol - not good for carburetor.

Wish it were better and ran on time in the suburbs.

Don't use public transportation.

Buses are sometimes not on time.

Have senior citizen transportation.

Good access to bus service.

Good access to bus. No problems.

Convenient and reasonable price for MTC bus.

Really need Metro Mobility -broke hip and they said not eligible to use. Bus always on time.

Very good bus service.

No Metro Mobility access, but does not currently use.

Everything is okay.

Good public bus here. Metro Mobility is good - does not want it cut, does not abuse it by using it for personal activities - just to go to the doctor.

I-35 is a joke.

Lucky - end of bus route outside building.

MTC wonderful, good service. Cheap fare doesn't start early enough if going to the doctor. Waits until cheaper fares valid.

Take city bus when no car. Rates for seniors good - low activity fares good. Received good treatment from drivers. Do try to maintain schedules.

Ride with family or take the bus.

Bus comes to highrise twice a day - lucky.

Doesn't take the bus often.

I wouldn't know what I would do without my son.

Metro Mobility is a good thing.

Take the bus downtown - drive to stop.

Want cleaner bus, better service and would be willing to pay. Cars are worse than bus - not well kept up. People who drive are surly. Would rather take a bus.

Signed up for Metro Mobility - hasn't needed it yet. Glad it is there.

City bus service can be improved - to be on time.

Metro Mobility - keep it the way it was. Cost could be a concern.

Rude drivers on the road.

We always drive.

Bus line in front of building.

Can't complain about Metro Mobility.

Nice to use Metro Mobility in emergency. Sometimes they are late. Had a 10:30am appointment - didn't get there until 3:00pm.

Bus doesn't come often. Would have to go to France Ave (3 blocks) to catch a bus.

Just cope with it. Need more police control.

Van service is sometimes unpredictable and can cause problems for people using the service.

Would have more comments if did not own a car.

Bus company does not shovel off shelters enough. Take Metro Mobility instead. Metro Mobility is GREAT.

APPENDIX B.

Descriptions of Econometric Travel Behavior Models

APPENDIX B. Descriptions of Econometric Travel Behavior Models

1. Congestion Pricing Model

i) The Demand Model

We assume that, in the short run, individuals have three possible ways of avoiding the congestion fee: they can change their destination, trip-timing or mode choice. These three decisions are clearly joint decisions, and must, therefore, be modeled jointly. We use the nested logit model (McFadden 1973, 1978, Ben-Akiva and Lerman 1985), which relies on the principle that the joint probabilities of a set of choices is the product of a set of conditional probabilities and one marginal. In our example, we have:

$$P^{it}_{mkd} = P^{it}_{m\mid kd} \cdot P^{it}_{k\mid d} \cdot P^{it}_{d} \tag{1}$$

where *m, k* and *d* represent mode choice (auto alone, carpool, bus), trip timing (peak or off-peak) and destination (downtown or not), respectively, *i* represents the individual and *t* represents the particular trip. If we assume that each individual, *i*, derives utility for each trip, *t*, according to:

$$U^{it}_{mkd} = V^{it}_{mkd} + \epsilon^{it}_{mkd} \tag{2}$$

where $V_{mkd,}$ the systematic portion of utility, is linear and can be separated into V_{mkd}, V_{kd} and V_d, and the error terms follow a generalized extreme value (GEV) distribution, then the conditional probabilities in equation 1 can be expressed as follows:

$$P^{it}_{m\mid kd} = \frac{e^{V^{it}_{mkd}}}{\sum_{j\in M} e^{V^{it}_{jkd}}} \tag{3}$$

and

$$P^{it}_{k\,|\,d} = \frac{e^{V^{it}_{kd} + \gamma^{k} IV^{it}_{kd}}}{\sum_{l \in K} e^{V^{it}_{ld} + \gamma^{k} IV^{it}_{ld}}} \tag{4}$$

and the marginal probability is:

$$P^{it}_{d} = \frac{e^{V^{it}_{d} + \gamma^{d} IV^{it}_{d}}}{\sum_{h \in D} e^{V^{it}_{h} + \gamma^{d} IV^{it}_{h}}} \tag{5}$$

where M represents the set of all modes, K represents the set of trip timing decisions, D represents the destination decisions, IV_{kd} represents the "aggregate utility" associated with the joint trip timing and destination decisions, often referred to as the "inclusive value:"

$$IV_{kd} = \log\left(\sum_{j \in M} e^{V_{mkd}}\right) \tag{6}$$

and IV_d represents the aggregate utility associated with the destination decision:

$$IV_{d} = \log\left(\sum_{l \in K} e^{V_{kd}}\right) \tag{7}$$

This approach gives us a set of three logit-type models that are joined by the inclusive values. The system is best estimated using full information maximum likelihood (see, for example, Brownstone and Small 1989), but for practical purposes, it is often estimated using a sequential approach. We first estimate mode choice as a conditional logit (equation 3), then use the mode choice parameter estimates to estimate the inclusive value for the trip timing decision (equation 6). Next we estimate trip timing as a logit (equation 4) and use the parameter estimates to estimate the inclusive value of the destination decision (equation 7). Finally, we estimate destination as a logit (equation 5).

For our analysis, we assume that all nonwork trips are flexible enough that each individual makes a mode choice, trip timing and destination decision for each trip and that these decisions are independent for each trip. Note that by not allowing for potential correlation among trips taken by the same individual, we obtain inefficient, and possibly inconsistent, parameter estimates. Kanninen (1995) addresses this problem by estimating mode choice models using fixed and random effect error terms. These models are highly complex and computer intensive, and have not been used before in mode choice models. 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 the inverse of the number of trips an individual took.

Note that we assume that each trip is taken somewhere, by some mode, at some time; we do not allow individuals to vary the number of trips they take. This is, admittedly, an odd assumption, but it is made because the mode, time of day and destination are the primary ways to avoid the congestion fee.

We assume that work trips, in the short run, are fixed in terms of timing and destination, and individuals make only a mode choice for these trips. We furthermore, assume that parameters may differ between work and nonwork trips and estimate separate mode choice models for these two types of trip. Parameter estimates associated with equations 3-5 for work and nonwork trips are presented in Tables B.1-B.3.

Of particular interest are the coefficients on expected trip cost and the inclusive values. Because the linear portions of the logit models represent utility, these coefficients respectively represent the marginal utility of money from the mode choice portion of the model and the marginal utilities of the conditional aggregate utilities derived from the previous decision levels modeled. The full marginal utility of money can be derived as:

$$M_c = \frac{-1}{\beta_c \gamma^k \gamma^d} \tag{8}$$

where β_c is the coefficient on cost in the mode choice model and the γ's are the coefficients on the inclusive values, as defined above.

Table B.1: Multinomial Logit Mode Choice Model for the Twin Cities, 1990

	Work Trips (n = 6,607)	Nonwork Trips (n = 10,706)[1]
Variable Name[2]	Coefficient[3] (t-statistic)	Coefficient (t-statistic)
Alternative Specific Constant (Alone)	0.23* (1.76)	-1.00** (-11.71)
Alternative-Specific Constant (Bus)	-0.80** (-2.87)	-1.72** (-6.29)
Peak Hour Dummy (Alone)	-0.30** (-4.38)	0.15** (3.28)
Peak Hour Dummy (Bus)	0.46** (2.71)	-0.41* (-1.76)
Downtown Destination Dummy (Alone)	-0.87** (-3.47)	0.069 (0.54)
Downtown Destination Dummy (Bus)	0.77* (1.92)	1.58** (5.75)
Peak Hour & Downtown (Alone)	0.32 (1.08)	-0.42** (-2.49)
Peak Hour & Downtown (Bus)	0.071 (0.15)	1.97** (5.41)
Expected Trip Cost (All)	-0.20** (-4.40)	-0.34** (-8.70)
Expected Travel Time * Wage (All)	-0.019** (-2.36)	-0096 (-1.47)
Male (Alone)	0.48** (7.33)	0.54 (12.58)
Male (Bus)	-0.17 (-1.10)	-0.94 (-0.59)
Over 64 years of age dummy (Alone)	-0.24 (-1.15)	-0.17** (-2.43)
Over 64 years of age dummy (Bus)	-1.95** (-2.12)	-0.32 (-1.33)
Urban dummy (Alone)	-0.098 (-1.31)	-0.057 (-1.16)

Urban dummy (Bus)	1.14** (7.24)	1.23** (7.73)
# Vehicles / Household Adults (Alone)	1.53** (9.66)	1.49** (14.78)
# Vehicles / Household Adults (Bus)	-1.81** (-5.91)	-2.57** (-8.38)
Annual HH Income (scaled by # adults in HH) (Alone)	-0.00014 (-0.039)	0.011** (4.49)
Annual HH Income (scaled by # adults in HH) (Carpool)	0.0062 (0.73)	0.0045 (0.49)
Pseudo R^2	0.45	0.35

[1] Observations associated with different trips taken by the same individual were weighted by (1/number of non-work trips) so that each individual appeared in the sample with a total weight of one.

[2] The terms in parentheses indicate the alternative that the coefficient refers to: Alone = drive alone in vehicle; Carpool = drive or ride with at least one other person; Bus = take public bus.

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

Table B.2: Logit Model for Peak / Nonpeak-period Nonwork Trip Timing (n = 10,706)

Variable Name	Coefficient[1] (t-statistic)
Inclusive Value from Mode Choice Model	0.94** (13.13)
Trip Distance	0.046** (14.31)
Annual Household Income (scaled by # adults in HH)	-0.0014 (-0.62)
Male Dummy	-0.37** (-7.69)
Urban Dummy	0.13** (2.77)
Over 64 years of age Dummy	-0.21** (-3.12)
Constant	-1.12** (-17.17)
Pseudo R^2	0.023

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

Table B.3: Logit Model for Destination Choice (Downtown or Not) for Nonwork Trips (n = 10,706)

Variable Name	Coefficient[1] (t-statistic)
Inclusive Value from Trip Timing Model	0.90** (2.92)
Annual Household Income (scaled by # adults in HH)	0.038** (10.55)
Male Dummy	0.11 (1.45)
Urban Dummy	0.83** (11.11)
Over 64 years of age Dummy	-0.24* (-1.72)
# Vehicles / Household Adults	-1.10** (-6.03)
Constant	-3.18** (-19.34)
Pseudo R^2	0.049

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

The marginal utility of money can be used to weight an estimate of utility change to obtain a welfare measure in dollar terms. In our study, we estimate the change in utility associated with the introduction of a congestion fee as the change in utility associated with the final stage of the nested model (the destination model). Note that we must allow for individuals to change their destination choice when the price changes, so the appropriate utility measure is *not* simply V_d, but instead, must represent expected utility, which is a combination of the different choice probabilities. The appropriate expression is analogous to the inclusive values defined above:

$$IV = \log \left(\sum_{h \in D} e^{V_d} \right) \qquad \textbf{(9)}$$

We estimate *compensating variation* as:

$$CV = \mathrm{M}_c \left(IV^1 - IV^0 \right) \qquad \textbf{(10)}$$

where the superscripts 1 and 0 indicate the before and after values.

ii) The Supply Model and Equilibrium

Roadway congestion tends to have an exponential relationship with use. That is, as the volume of traffic increases, nearing capacity, congestion times increase at an exponential rate. The data show that trips with downtown destinations tend to take 10 minutes longer than other trips of the same length. We assume these 10 minutes can be mitigated at an exponential rate as the number of vehicles downtown during peak times decreases.

The demand and supply models are estimated using an iterative, sequential procedure. First, the demand model is estimated separately for work and non work trips assuming no supply-side (congestion time reduction) effect. This provides a first-order effect of the congestion fee: a reduction in vehicle trips to the downtowns during peak times. Then, the vehicle trip reductions are input into the supply-side model to obtain the reduction in expected travel times for those vehicles that remain in the system. The demand model is then re-estimated using the updated expected travel times. This results in slightly revised vehicle reduction estimates. The procedure is repeated until an equilibrium is reached between the demand and supply-side models.

2. Gasoline Tax and Bus Fare Reduction Models

Individuals can avoid gasoline taxes in only one way: by driving less. They can take advantage of bus subsidies by traveling more by bus. We model two choices individuals can make in response to these price signals: mode choice and number of trips. Instead of number of trips, we might have modeled total vehicle miles traveled (Krupnick, Walls and Hood 1993) but we chose to remain consistent with the other parts of our demand model which take trip distance as given and concentrate on trip choices. Cameron (1994) also models trip frequency as opposed to VMT. The mode choice models used are identical to the ones described in the congestion pricing model (Table B.1).

We assume that individuals are constrained, in the short run, to having to take all work and school trips they presently take. We therefore model the number of nonwork trips as the relevant travel choice variable. Number of trips is estimated using a method that accounts for observations with zero observed levels of consumption. A significant percentage of the sample population recorded no nonwork trips on the particular day they were surveyed. But it would be inappropriate to model the data as if these individuals average zero nonwork trips per week. If, for example, an individual takes trips three days per week, then there is a 3/7 chance that they would have taken trips on the particular day they were surveyed. If this person recorded a trip, then we would have an overestimate of that persons trip-making. On the other hand, if that person recorded no trip, then we would have an underestimate. In either case, the appropriate estimation technique should adjust for this "lumpiness" in consumption.

We estimate number of nonwork trips using a "frequency of purchase" method (Meghir and Robin 1992). First, we estimate a probit model on a dummy variable that is equal to one if the individual recorded at least one nonwork trip. The coefficient estimates from this model are presented in table B.4. Then we use the model to predict the probability that an individual takes a nonwork trip on any given day. This predicted probability is multiplied by the observed number of trips for those observations that have a positive number of trips to obtain an *expected* number of trips. Finally, we regress the log of this expected number of trips using ordinary least squares, and include the inclusive value from the mode choice model as one of the regressors.

This joint mode choice/number of trips model is not utility-theoretic as is the nested logit model used in the congestion pricing model, but it is assumed to be a reasonable ad hoc procedure. Parameter values for the number of trips model are presented in table B.5.

Since the gasoline tax does not target any particular areas or times of day, it is assumed to reduce vehicle use in a diffuse way, so that congestion levels are unaffected. Bus routes tend to be focused toward the center cities and increased use might, in fact, reduce congestion in these areas. However, due to data limitations, we do not investigate this possibility here. We assume the changes in demand are sufficiently small to be approximated by the demand model without supply-side effects.

Table B.4: Probit Model for Probability of Recording at Least One Nonwork Trip (n=8,798)

Variable Name	Coefficient[1] (t-statistic)
Annual Household Income (scaled by # adults in HH)	0.0064** (3.49)
Male Dummy	0.079** (2.41)
Urban Dummy	-0.0075 (-0.20)
Over 64 years of age Dummy	-0.46** (-10.20)
# Vehicles / Household Adults	0.26** (3.88)
Constant	0.73** (12.99)
Pseudo R^2	0.24

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

Table B.5: Log-Linear Model - Number of Nonwork Trip (n=6,794)

Variable Name	Coefficient (t-statistic)
Average Inclusive Value from Mode Choices for All Trips Taken	0.033** (2.70)
Annual Household Income (scaled by # adults in HH)	-0.0020** (-3.396)
Male Dummy	-0.069** (-5.95)
Urban Dummy	-0.033** (-2.71)
Over 64 years of age Dummy	-0.076** (-4.34)
# Vehicles / Household Adults	-0.034 (-1.29)
Constant	0.18** (9.30)
R^2	0.011

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

3. Comments about the Travel Behavior Models

This report uses state-of-the-art transportation demand models to evaluate the impacts of pricing automobile use. The econometric models are intended to fully capture the relevant decisions that will be affected by each pricing policy. Several innovations have been introduced in this section that will be relevant contributions to the academic literature. Examples are: the technique of estimating demand and supply models iteratively to obtain an equilibrium outcome; and the use of the "frequency of purchase" method to account for the lumpness of the number of trips variable. All behavioral models are subject to qualifications though. The following summarizes qualifications associated with the econometric model, the statistical procedures and the data.

The model used in this analysis is the nested logit model which is used frequently in the transportation demand literature because of its simplicity and elegance. However, the model is limited in terms of its flexibility and can predict some unrealistic phenomena. If, for example, the price of bus increases, then the model will always predict that both driving alone and carpooling will increase by identical proportions. In other words, all cross-price elasticities with respect to one mode are identical. This is an unrealistic prediction that has led researchers to question the adequacy of the logit model for predicting behavior.

The models are estimated using a sequential procedure. The separate components of the models are estimated independently with shared variables being passed from one component to another as they are estimated. This technique is quite common in the literature when complex models, such as the ones presented here, are estimated. But it is well-known that the appropriate procedure is to estimate all the components of a model simultaneously using full information maximum likelihood. This technique is feasible but rarely used because of the computational burden. The estimates obtained using the sequential technique are inefficient, but consistent.

It is also important to bear in mind that anytime an econometric model is used to predict behavior with respect to a price that is outside the range of the available data, the predictions can only be considered order of magnitude approximations. The congestion fee that is introduced in this report increases the price for peak hour travel to downtown destinations. The data do not reflect price variability over times of day or destination. The model may, therefore, not adequately predict the behavioral response to such changes. Better estimates of responses will require real experiments with congestion pricing.

APPENDIX C.

The Use of TRANPLAN and EMIS Models

APPENDIX C. The Use of TRANPLAN and EMIS Models

The following is a description of the models used to forecast traffic patterns and generate emissions estimates as provided by Kevin Roggenbuck, Transportation Planner, Metropolitan Council.

Met Council staff used its TRANPLAN regional travel model to reduce the number of trips in each scenario, as described in Section 3. The revised trip tables and loaded networks were then run through the regional emissions model, EMIS, to estimate the reduction in carbon monoxide emissions of each policy.

Travel forecasting follows a basic four-step approach: trip generation, trip distribution, mode choice, and network assignment. Each step is briefly described below.

The trip generation model estimates trip productions and attractions. The Twin Cities travel model has seven different trip types, each related to work, school, shopping, or other trip purposes. The travel model also estimates the number of trips that occur, by type, for six time periods. When combined, the six time periods equal a 24-hour day. The first part of trip generation estimates the number of productions, or trips that begin or end at the place of residence. It is primarily based on household information such as automobile availability, income and family size. The second part estimates the number of attractions, or trip ends anywhere except the place of residence. This is based primarily on the number and type of jobs in the area and school enrollment. The Twin Cities region is divided into 1,165 traffic analysis zones. Each zone contains socioeconomic information, such as the number of households, total employment, school enrollment, etc. that is used in the trip distribution model described below. The model also contains 35 external stations where trips enter and leave the region.

The trip distribution model takes all the trips from the trip generation model and distributes them from zone to zone based on travel time, travel cost, accessability, and the relative "attractiveness" of each zone. This is done through the Gravity Model. The trip distribution process also includes trips with an origin or destination outside the seven-county area, and trips that pass through the region.

The TBI and the 1990 bus on-board survey were used in the mode choice validation to develop target levels of bus ridership and ridesharing. The surveys were designed to show trip purpose, trip destination, and household car ownership, creating an accurate representation of travel.

After the model distributes trips from zone to zone and divides them into vehicle trips with one occupant, two or more occupants, and bus trips, it sends them there on the regional highway network. Based on the physical characteristics of the network, such as speed and capacity, the model assigns trips along paths based on the shortest travel time. The network assignment phase is done for the AM peak, PM peak, and off-peak periods.

Daily Trip Generation:

The base year 1990 trip tables for all trip purposes were factored to reduce the total number of trips by the percentage derived for each of the three scenarios. Since the regional travel model has 1200 internal and external zones, the trip table for each time period is a 1200 x 1200 matrix. Due to rounding, the trip reductions in Tables C.1. and C.2. are not exactly as described for each scenario; however, they are within 1,000 trips, or .001%.

Table C.1: Total Daily Trips: 1990

	Base 1990	Congestion Fee	Gasoline Tax	Bus Fare Reduction
Total Trips	6,478,702.00	6,467,529.00	6,467,903.00	6,449,087.00
Change		-11,173.00	-10,799.00	29,615.00
% Change		-0.17%	-0.17%	-0.46%

Peak Period Trips:

The congestion fee scenario produces a 9.74% decrease in peak period trips entering and exiting the central business districts of Minneapolis and St. Paul. The AM Peak Period in Table C.2 extends from 6:00 AM to 8:00 AM. The AM peak period includes the AM peak hour from 6:30 to 7:30 and the AM peak shoulders. The PM Peak Period shown below begins at 3:00 PM and ends at 6:00 PM. The PM peak period includes two consecutive PM peak hours, from 3:40 to 5:40, and the PM peak shoulders. The peak periods analyzed in this scenario do not match the time periods assumed in Section 3, and are an hour longer. The emissions impacts should therefore be considered order of magnitude estimates rather than point estimates.

Table C.2: Peak Period Trips To and From the CBD's: 1990

	1990 Base			
Time Period	Trips	Trips	Change	% Change
AM Peak Period	34,950	31,647	-3,303	9.45%
PM Peak Period	80,614	72,744	-7,870	9.76%
Total	115,564	104,391	-11,173	9.67%

Projected Trips in the Year 2000:

Tables like C.1 and C.2 were produced using the procedures described above with additional assumptions about travel behavior and the highway network in the year 2000.

Air Quality Analysis:

In both the 1990 and 2000 time frames, the revised trip tables for the baseline condition and each scenario were run through the network assignment portion of the travel model. MOBILE 5.0a was used to estimate emission factors based on local conditions and fleet age and mix. The loaded highway networks were run throught EMIS to calculate CO emissions.

APPENDIX D.

Recommendation for Future Travel Behavior Inventories

APPENDIX D. Recommendation for Future Travel Behavior Inventories

Like all survey data sets, the 1990 Travel Behavior Inventory for the Twin Cities cannot provide all researchers with the exact variables they might like to have. This appendix provides a list of variables that are not available in the 1990 survey, but that might be incorporated into later surveys to make them more useful for environmental policy analysis. There is an inverse relationship between length of survey and probability of response which must be considered when designing the actual survey.

- Total trip cost. Accurate assessments of travel expenditures are necessary for a reliable pricing policy analysis. Total costs should include parking cost, estimate of gasoline cost, bus fare, carpool contribution, miscellaneous expenditures.

- More detailed trip purposes. We are seriously lacking in understanding which trips are considered essential and which are discretionary. Purpose categories might be expanded to include such things as entertainment/recreation and personal business errands. More importantly, there could be questions about the importance of trip timing and destination. For example, "Do you have an appointment or schedule to keep, or could this trip be taken at another time?" or "Is there an alternative destination with similar amenities? How much closer or further is it from your origin?"

- More detailed personal characteristics. Does individual have handicap that affects ability to drive? Access to a car? What is his or her race?

- Details about car. Make and model of car and estimated gas mileage. Has it passed or been waived for inspection? This information can be used to estimate environmental impacts.

- Value of travel time information. We still do not understand how much time affects peoples' decisions about travel and the "costs" they experience due to congestion. The individual could be asked to calculate his or her "wage rate," and whether he or she finds driving pleasurable or unpleasurable.

- Route choice information. To do a proper congestion pricing model, we need to model route choice, primarily whether or not an individual used one of the major corridors for their trip and which one.

- Bus information. To better model bus choice, we need information on how feasible a bus trip is, how far is the bus stop from the house and workplace, and is a transfer involved in the trip.