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Theoretical Basis and Parameter Estimates for the Minority Transportation Expenditure Allocation Model (MITRAM)

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Center for Transportation Research

Energy and Environmental Systems Division
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FOREWORD

In 1979, the U.S. Congress created the Office of Minority Economic Impact (MI) within the U.S. Department of Energy (DOE) out of concern for the effects of energy shortages and rising prices on minority citizens. The legislation [42 U.S.C., Sec. 7141 (c)] defines a minority group as one consisting of black, Oriental, American Indian, Eskimo, or Aleut citizens, or Puerto Rican or other Spanish-speaking citizens of Spanish descent. This law requires MI, among other things, to conduct research to (1) determine the average energy consumption and use patterns of minority groups relative to other population groups and (2) evaluate the percentage of disposable income spent on energy by minority groups relative to other population groups.

As part of its compliance with this mandate, MI commissioned Argonne National Laboratory (ANL) to conduct a multiyear research program to determine energy consumption and expenditures by minority groups. The ANL program consists of three tasks:

- Assemble a data base and develop the tools to assess the effects of government energy policies and programs on minority groups.

- Assess the effects of government programs on minorities and identify options for modifying those programs (e.g., through policy, regulatory, or legislative changes) to alleviate possible hardships for minority groups.

- Assess the effects of key macroeconomic variables on the pattern of U.S. energy demands and expenditures, according to demographic groups.

This report is one of a series produced by ANL in the performance of these tasks. It is directed at transportation and energy researchers, as well as policy analysts and other investigators who share an interest in the characteristics and behavior of minority households.

Further information on the overall MI research program can be obtained from Georgia Johnson, the research project officer for the DOE Office of Minority Economic Impact, or from Argonne National Laboratory. Information on this report may be obtained directly from the authors.

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ABSTRACT

This report documents research to estimate coefficients for the Minority Transportation Expenditure Allocation Model (MITRAM) equations. The estimation process is described in terms of the types of data needed and the utility of the resulting coefficients. Using these coefficients, the MITRAM model produces reasonable estimates for transportation energy consumption for average U.S. black and white households based on a range of real gasoline prices similar to those experienced from 1981 through 1986. The model predicts reactions to sustained fuel price changes for as long as a decade after the change.

1 INTRODUCTION

The MInority TRansportation Expenditure Allocation Model (MITRAM) of vehicle and transportation energy consumption identifies and accounts for differences in minority (black and Hispanic) and majority (white) patterns of household-based vehicle holdings and transportation energy consumption.[1] The model has been formulated so that its inputs are the same as those used in the Minority Energy Assessment Model (MEAM) of Argonne National Laboratory, which projects residential energy consumption by minority status and fuel type in four census regions. In its present form, MITRAM is designed to estimate transportation fuel expenditures and out-of-pocket public transportation expenditures for an average U.S. household. However, during construction of the MITRAM equations, an effort was made to estimate coefficients so that projections for low- and high-income households would also be accurate.

Several data sources were used during the development of submodels within MITRAM. Surveys such as the Nationwide Personal Transportation Studies (NPTSs) of 1977 and 1983 and the Residential Transportation Energy Consumption Surveys (RTECSs) of 1983 and 1985 were used for cross-sectional analyses. National time-series data were obtained from reports published by the Bureau of the Census and the Bureau of Labor Statistics (BLS). Data published by these organizations use four racial groups: white, black, American Indian (including Eskimo and Aleut), and Asian and Pacific Islander; data are also reported for separate Spanish-origin (Hispanic) groups that may be of any race. Thus, the Hispanic category is overlaid on the four racial categories.

In our analysis of survey data, households were classified by race and origin of the head of the household as white, black, Hispanic, or other. *White* excludes Hispanics. *Black* includes black Hispanics; *Hispanic* includes all other Hispanics. *Other* includes native Americans (American Indian, Eskimo, and Aleut) and Asian and Pacific Islanders. When data are supplied or projected by race, the term *race* refers to whites, blacks, and Hispanics as defined for our analysis of survey data. Some attributes, such as gasoline price, urban consumer price index, new car rated fuel economy, and new and used car price indexes, are not race-specific. These values are applicable to white and black households as well as to households of all of the categories listed above.

The model development effort covered white, black, and Hispanic households. Hispanic households have been analyzed in this report, but the current operating version of MITRAM generates estimates only for white and black households.

MITRAM uses detailed household data, fuel price projections, and estimates of public transportation use to estimate the numbers of vehicles held by households. Then the vehicle-miles of travel (VMT) of those vehicles is estimated. Fuel price projections and other variables are used to estimate changes in the fuel efficiency of new vehicles. A unique feature of the MITRAM fuel efficiency equation is that it estimates a long-term technological response to fuel price increases. Fleet fuel economy is modeled as a simple function of new-car fuel economy.

From estimates of vehicle fuel economy and the cost of fuel, MITRAM generates aggregate and disaggregate (by minority status) national projections of transportation fuel consumption per household and shares of income devoted to fuel expenditures. To these are added estimates of out-of-pocket local public transportation expenditures per household, including commuter rail, local public transit, and taxicabs. These have been included because minorities are far more dependent on local public transportation than is the population in general. Because minorities are more likely to shift spending from private vehicles to public transportation when fuel prices rise and economic conditions worsen, a model that examines only minority spending on motor vehicle fuel would probably understate the effects on minority households. The total of motor fuel and public transportation expenditures thus provides a rough estimate of out-of-pocket costs for essential trips. Intercity trips other than by automobile are not included in these estimates.

Our approach involved, as much as possible, construction and statistical comparison of equations to determine the appropriate coefficients for variables in the MITRAM equations. This approach was a pragmatic response to (1) shortages of price information in the most detailed cross-sectional data sources describing household behavior and (2) an absence of minority detail in the time-series sources describing average U.S. behavior. The NPTS, a cross-sectional data base, is conducted only every few years and does not include information on census region, vehicle purchase cost, gasoline cost, or public transportation cost. The use of national time-series data allows the latter three costs to be incorporated into MITRAM, but to date has not allowed direct incorporation of regional detail.

In principle, the absence of regional detail is a problem, but in comparison with variations in residential energy consumption, the degree of variation in VMT explained by the census regions is statistically insignificant.[2] Similarly, regional variations in oil product costs have clearly been far smaller than the temporal variation in costs over the last two to three decades (see Ref. 3, "Sales Prices of No. 2 Distillate to Residences," any issue). To the extent that regional characteristics of households could be introduced into MITRAM, regional detail could be generated.

Cross-sectional equations for household behavior were constructed from the 1977 and 1983 NPTSs to estimate the responses of households in terms of variation in vehicles held, VMT per vehicle, income (1983 dollars), education and age of the household head, transit availability, workers and nonworkers per household, and urban vs. rural location. Some of these variables that were not used in MITRAM were used in other equations based on the NPTS data base.

It was desirable to include as many theoretically important variables as possible in the NPTS-based equations, although it was also desirable not to use pairs of collinear variables measuring essentially the same attribute. This design of the equations reduced the likelihood of bias in the estimated coefficients used in MITRAM. Dummy variables were used to test for differences between coefficients based on 1977 and 1983 data. In principle, the use of dummy variables would allow for the influence of factors not measured by NPTS, such as fuel price and vehicle cost. The 1983 NPTS[4] was about one-fourth the size of the 1977 study,[5] so even using dummy variables, the 1977 NPTS data probably dominated the estimates of the coefficients. Since there were about 20,000 observations in the combined NPTS samples, we could test equations with a large number of independent variables; in the NPTS-based vehicle-holding equation, for example, there are 17.

In contrast, the time-series equations are based on national aggregates for each year and contain only about 20 to 30 data points for each variable. Consequently, the use of many independent variables was impossible because of the lack of adequate degrees of freedom and the absence of detail in the annual national statistics. When it was possible to construct both an NPTS-based cross-sectional equation and a comparable time-series equation, the most important household variables from the former were tested for inclusion in the time-series version. Transportation-related price variables were added to the time-series equation so that, after controlling for transportation prices, the influence of household characteristics could be estimated. The most important variables common to the NPTS and the time-series equations are household income, number of workers, number of cars, miles driven, and number of persons per household. Different variables relating to transit were used in the cross-sectional and time-series equations.

In the case of public transportation spending, minority detail was "backed out" by combining minority-specific information from the NPTS with the national averages from the Personal Consumption Expenditure Survey (PCE) of the BLS.[6] The national PCE data for public transit and commuter rail were disaggregated to race-specific numbers based on the assumption that spending per household would be proportional to the number of trips.

Statistical tests were used to determine whether the equations support the hypothesis that there is an interactive effect between a given pair of variables and, if an effect was indicated, to determine a good estimate of the magnitude of that effect.

Ideally, a single coefficient would be adequate to describe both how national aggregates change from year to year and how a given household changes when its household characteristics change. The model, in its present form, focuses on describing national aggregates. However, given the relatively large differences between national average household income, employment, and size for whites and minorities, it is necessary that the model accurately capture the cross-sectional NPTS information on the effects of household attributes.

The modeled direction of an effect between two variables -- its causal structure -- is in nearly all cases a matter of statistically supported prior expectations. Most of those expectations, in turn, rest on basic economic theory -- primarily that if price goes up, consumption will be reduced, whereas if income goes up, consumption will be increased. However, that there are some complexities to these simple truths. In MITRAM, the primary questions are *when* and *by what means* consumption is altered within various racial and income categories. For example, after a gasoline price increase, do consumers decrease fuel consumption in proportion to the increase? If so, do they do so immediately or is there a lag? If there is a lag, is it longer for minorities than for the rest of the population? Is the lag affected by consumer decisions only, or do lags in product offerings restrict the consumers' options? Do households substitute public transportation for private vehicles, or do they primarily cut back on travel?

These questions cannot, to the best of our knowledge, be answered simply through statistical tests of single equations, or, given the lack of detail in the available data, by constructing a set of simultaneous equations. One way of addressing these questions is to construct a complex model of the anticipated interactions by assembling a series of simple models of the components of the process. Statistical tests for anticipated lags can be conducted to the extent the available data allow. When multiple tests support the existence of simple paired relationships among variables, those relationships may be appropriately introduced into the model. The model can then estimate how the more complex interactive effects combine to affect the time path of transportation expenditures by households after fuel price changes.

2 MODEL STRUCTURE

This section provides information to help assess the reasonableness of regression equations developed from the two NPTSs and from national time series. In principle, comparing the 1977 and 1983 NPTSs provided an opportunity to understand the reactions of households to the nation's most severe gasoline price increase of the century. In reality, the reliability of the comparison was compromised by a change in the 1983 NPTS question regarding how much the vehicles in the household had been driven. When the NPTS household estimate of VMT was compared with the values from NPTS trip file diaries, the two did not agree. The household estimates indicated that poorer households had sharply increased the number of miles driven from 1977 to 1983, in spite of higher fuel and vehicle costs,[7] but the trip file indicated more logical behavior, namely a reduction of travel. When these results were used to estimate probable changes in national VMT and were compared to national VMT statistics of the Federal Highway Administration,[8] the trip file estimates were low and the household estimates were high. Therefore, we decided to rely on coefficient estimates from the national statistics for VMT. Given the drawbacks of the NPTS (in terms of availability of price information and reliability of VMT information), we examined other sources of data on patterns of change in transportation costs, demographic structure, and consumer income during 1977-83 period, relating changes in vehicle purchase patterns and VMT to the changes in these variables.

Microeconomics suggests that two parts of the consumer response to changes in fuel prices are the substitution effect and the income effect. The substitution effect accounts for the degree to which other goods are substituted for fuel, holding consumer welfare (utility) constant. The income effect accounts for the fact that, if fuel prices increase and other prices and consumer income remain the same, consumers will be worse off. Both the vehicle-holdings equations and the VMT equations include income as a variable, along with variables directly or indirectly related to gasoline price. However, no measure of consumption of "other goods" is included in these equations or in MITRAM, so the degree of substitution of other goods for transportation is not estimated. Nevertheless, this microeconomic framework has been used conceptually in that both income and intratransportation-sector substitution effects of several types are approximated by the model.

The existence of a second (and perhaps more important) income effect from energy price shocks has been proposed recently in popular economic theory.[9] The microeconomic income effect assumes that nominal income remains constant. However, a recent economic textbook states that supply shocks such as sharp oil price increases have a negative effect on the macroeconomy, and it includes sections devoted to this effect.[10] Several analysts have shown a macroeconomic income effect in which energy price shocks statistically precede declines in real national output (and by inference, in real income of households) with about a one-year lag (see Ref. 11 for further discussion). This implies that the real income of households is reduced through both the microeconomic and macroeconomic effects of energy price increases. It should be emphasized that MITRAM does not estimate the macroeconomic supply shock effect. The estimation of household income was not an objective of this study, and MITRAM uses exogenous estimates of gasoline price and household income. If the model which supplies income figures to MITRAM does not properly estimate the degree of decline in average household income after severe energy price increases, MITRAM will not generate accurate estimates of the transportation fuel expenditures of average households.

The basic questions about within-household microeconomic reactions to energy price can be termed income and substitution questions: first, did welfare (utility) appear to be reduced by the rise in energy prices that occurred from 1977 to 1983, and was there evidence of a differential effect on minorities? and second, given the income effects suffered by minorities, is there any evidence that they substituted other goods for travel and vehicles any differently than whites?

2.1 HOUSEHOLD CHARACTERISTICS, 1983

We begin by comparing white and minority mean household characteristics from the 1983 NPTS data base and showing whether the groups are statistically different (Table 1). On the average, black households were statistically different from whites in each of the eight attributes listed, while Hispanics were significantly different in seven of the eight. "Other" minority households differed significantly from whites in only four attributes. The differences between black and Hispanic households were significant in every case. Based on the 1983 NPTS, minority households are consistently larger than white households, they drive fewer miles and they live where they have better access to transit. For households within two miles of transit, black and Hispanic households live closer than white households. The heads of minority households are consistently younger than those of white households, and black and Hispanic household heads have less education than white household heads. Hispanics have more workers per household than blacks; as a result, Hispanic households must own more cars to get to work and they must drive more.

2.2 INCOME EFFECTS, 1977-83

The real household income of whites and minorities dropped sharply from 1977 to 1983, and the income of blacks and Hispanics dropped more sharply than that of whites (Ref. 12, 1986, p. 445). In 1984 constant dollars, the median household income of whites dropped by 6.7% from 1977 to 1983; the median for blacks dropped by 10.1% and that for Hispanics by 9.8%. Correspondingly, the proportion of households living in poverty (less than $10,000 in 1984 dollars) increased for all three groups, but more for minorities than for whites. The proportion of whites in this category increased from 0.178 to 0.197 (a 10.7% increase in the proportion) from 1978 to 1983, the proportion of blacks increased from 0.358 to 0.406 (a 13.4% increase), and that of Hispanics, from 0.241 to 0.311 (a 29% increase).

Information on job growth per household implies that Hispanic households suffered real income losses even though they increased the number of jobs held to the point that they held more jobs per household in 1983 than whites. In 1977, the number of

TABLE 1 Mean Household Attributes for Whites and Minorities (1983 NPTS)

Attribute	White	Black	Hispanic	Other
Number of persons	2.61	2.89 (3.90*)[a]	3.63 (8.71*) (5.60*)	3.12 (3.38*)
Age of head (years)	48.0	46.3 (-2.31*)	41.3 (-7.30*) (-4.49*)	40.9 (-5.42*)
Education of head (year of school)	12.8	11.0 (-11.64*)	10.2 (-9.44*) (-2.71*)	13.3 (1.34)
Number of workers	1.20	0.93 (-7.41*)	1.30 (1.76) (5.54*)	1.36 (1.98*)
Vehicles owned	1.79	0.99 (-18.99*)	1.46 (-4.67*) (6.05*)	1.64 (-1.40)
Vehicle-miles of travel per year (thousands)	17.02	8.38 (-16.04*)	13.13 (-3.87*) (4.56*)	15.83 (-0.85)
Access to transit[b]	0.60	0.79 (11.19*)	0.83 (10.06*) (1.58)	0.86 (8.52*)
Distance to transit[c] (blocks)	4.40	3.02 (-9.33*)	3.66 (-2.66*) (2.20*)	3.83 (-1.58)

*Means are different with 95% certainty.

[a]T-values (in parentheses) compare minorities to whites; the second value for Hispanics compares blacks and Hispanics.

[b]Value is one if less than 2 miles, zero if 2 miles or greater.

[c]For households less than 2 miles from transit.

jobs per household for whites was 1.22, for blacks 1.07, and for Hispanics 1.23 (Ref. 12, 1984, pp. 406, 459). By 1983, this figure had dropped to 1.20 for whites and 1.01 for blacks but had increased to 1.27 for Hispanics (Ref. 12, 1986, p. 391, 445). If these figures are divided into the corresponding median incomes, the median household income per worker for Hispanics in 1983 was $12,950 (1984 dollars), a figure only slightly higher than the $12,844 for blacks. This represents a sharp drop of 13% in median real household income per worker for Hispanics from 1977 to 1983, a value well in excess of the 5% drop for blacks and whites. The validity of these numbers is supported by the earlier figures on changes in the proportion of households in poverty.

Although median income per household and per worker dropped from 1977 to 1983, the mean income per worker stayed almost the same. When the total national value of personal income for 1977 and 1983 is divided by the total number of workers employed and the 1977 value is inflated to 1983 dollars using the Consumer Price Index (CPI), mean personal income per worker was $27,515 in 1977 and $27,213 in 1983, a decline of 1%. This implies that income distribution was altered so that the lower income categories suffered reductions in worker income and increases in worker numbers. Workers with incomes below the mean in 1983 had typically lost real income between 1977 and 1983.

In contrast, individual workers with incomes higher than the mean in 1983 had gained real income per employed person during the same period, and typical workers in this category had gained more real income than typical workers lower than the mean in 1983 had lost. The "above-mean" category had to represent a smaller proportion of workers in 1983 than in 1977, so that the cumulative gains for workers with large real increases in income simply offset the cumulative losses of the larger number of workers with smaller individual losses. Thus, workers with income below the mean in 1983 represented a larger proportion of the employed population than did the same group in 1977, and a significant minority of high-income workers had moved into the low-income group.

In summary, although real income per worker was about the same in 1983 as in 1977, real income per household declined because of a decline in number of workers per household in black and white households and because of a sharp decline in income per worker in Hispanic households. There were relatively more households living in poverty in 1983 than in 1977, and median income per household in all three categories dropped.

Based on our examination of the group of 1977 NPTS nonretired households whose current income reflected their permanent income reasonably well (see Ref. 7 for a discussion of sample group construction), the effect of rising income is to increase the total number of private vehicle trips taken over all income ranges. The effect of increasing income on the use of transit, commuter railroads, and taxis is not so simple. The number of trips taken in public vehicles increases as household incomes move from the less-than-$10,000 category to the $10,000-24,999 category. For the above-$25,000 income category, the total number of trips of this type declines (see Table 2).

TABLE 2 Estimated Total Number of Trips per Household per Day, by Income and Race (from the NPTS data, nonretired heads)

Household and Income (1983 $, thousands)	Total Trips		By Private Vehicle		By Nonprivate Vehicle[a]		Other Trips	
	1977	1983	1977	1983	1977	1983	1982	1983
All								
<10	3.1	2.8	1.5	1.0	0.15	0.15	1.46	1.58
10-24.9	5.3	4.8	3.9	3.4	0.22	0.17	1.20	1.28
>25	7.1	6.3	5.7	4.9	0.18	0.14	1.22	1.25
White								
<10	2.9	2.8	1.5	1.2	0.08	0.07	1.36	1.52
10-24.9	5.3	4.8	4.0	3.5	0.16	0.10	1.12	1.24
>25	7.2	6.4	5.8	5.1	0.16	0.10	1.19	1.23
Black								
<10	3.4	2.6	1.4	0.5	0.34	0.32	1.73	1.76
10-24.9	5.4	4.8	3.3	2.7	0.52	0.52	1.55	1.66
>25	6.5	5.8	4.7	3.7	0.46	0.65	1.46	1.46
Hispanic								
<10	3.4	2.8	1.6	0.9	0.24	0.25	1.56	1.60
10-24.9	5.4	4.8	3.3	3.2	0.51	0.40	1.60	1.27
>25	6.1	5.8	4.5	4.3	0.27	0.10	1.31	1.36

[a]Local transit, commuter railroads, and taxis.

2.3 SUBSTITUTION EFFECTS

Between 1977 and 1983, among the most important energy price changes (which caused many of the income changes discussed above) was the 13% real increase in gasoline price (Ref. 13, p. 139). The worst of the increase (60% in real terms) occurred between 1978 and 1980, after which economic conditions deteriorated rapidly, with two recessions in the 1980-82 period.

The average transaction cost for new U.S.-manufactured passenger cars that consumers purchased increased in real terms by 7.7% from 1977 to 1983 (Ref. 14, 1986). The MITRAM list price index for new cars, which was constructed specifically for this study, rose by 22.9% over this period after deflation by the aggregate urban consumer price index (CPIu). The MITRAM index, which is based on the BLS new car price index up to 1973 and then a sales-weighted list price for the four most popular car types in each of the five U.S. Environmental Protection Agency (EPA) size classes thereafter, does not adjust for technical change or for the net cost of new cars after trading used cars. It provides a better indication of the sales of new cars and holding of cars by households than did the BLS new car price index. Consumers apparently held the transaction cost for all new cars down by shifting away from the most expensive (and lowest-fuel-economy) automobiles. The share of new car sales represented by large cars declined by 10.1% from 1977 to 1983, and the share of subcompacts and minicompacts increased by 2.2%.[15] The most significant consumer shift, however, involved substituting small pickup trucks for cars.

The real cost of used cars, which are more likely to be purchased by low-income minorities, rose faster than the transaction price of new cars and slower than the MITRAM list price index, increasing by 9.6% over the period 1977-83 (based on a 1983-constant-dollar, CPIu-deflated, used car index incorporating the BLS used car price index). Those lower-income households that attempted to substitute public transportation for vehicle ownership were also faced with a 10% increase in real costs of public transportation. The sharpest increases in used car and public transportation costs occurred just after gasoline prices had increased sharply. From 1980 to 1983, real used car costs rose by 31%, public transit costs by 23%, and commuter rail costs by 22%. During this period, real new car list prices rose by 31.5%, according to the price index used for this study.

New cars in 1983 were more fuel-efficient than those available in 1977, 24.2 miles per gallon (mpg) in 1983 vs. 17.2 mpg in 1977, an increase of 41% for new cars in the domestic fleet (Ref. 16, 1984, p. 73). However, because time is required to replace old vehicles, fleet fuel economy increased only from 13.9 mpg to 16.7 mpg, an increase of 20%. With the new fuel efficiency, the annual use of cars purchased new (as estimated in the 1983 NPTS; Ref. 17, p. 4-23), and the 1983 car loan rate of 12%, it would have taken a consumer approximately six years to recover through reduced fuel costs the added cost of a 1983 car relative to a 1977 car (based on the rise in transaction cost of new cars). As a result of the combined effects of the 1978-80 fuel price increase and the Corporate Fuel Economy Standards (CAFE), the automobile industry had by 1983 provided a more fuel-efficient car, although at an increase of 7.7% in real transaction cost and 22.9% in real list price.

Between 1977 and 1983, real household income dropped and interest rates on car loans rose, substantially reducing the affordability of new cars. One response was to increase the length of finance periods, allowing monthly payments to remain almost constant as a share of income. In 1977, the average annual new car loan payment was 11.4% of median income and in 1983, only 11.8%, with a corresponding extension of the average loan maturity from 40.7 to 45.9 months, a 13% increase (Ref. 14, 1986). Consumers who purchased new cars in 1983 drove those cars 18% more miles in the first two years of use than buyers of new cars in 1977 (Ref. 17, p. 4-23). Apparently, only persons who drove more than average could justify buying a new car, because only they were able to get a good return on their investment through better fuel economy. With only this limited group able to justify purchasing a new car, new car sales dropped rapidly.

In 1983, the number of cars and trucks less than four years old dropped by 14% from that in 1977, while the number of cars and trucks greater than four years old increased by 30% (Ref. 16, 1978 and 1984). Used car demand apparently increased sharply, resulting in reduced scrapping rates (Ref. 16, 1986) and higher used car costs. Passenger car scrapping dropped from 8.23 million units in 1977 to 6.24 million in 1983, a drop of 24%. Scrapping jumped by 18% from 1978 to 1979, reaching its 1977-1983 and all-time peak, probably because the price shock made many low-mpg cars obsolete. (Scrapping had also jumped to an all-time peak during the 1973-74 oil price shock and dropped sharply during the ensuing recession.)

Prices of used cars sold at wholesale auctions increased in real terms by 16% from June 1977 to June 1983 (Ref. 18, April 24, 1985, p. 56), and the average real amount financed increased by 12.5% (Ref. 16, 1986). On this basis, the cost increase was greater than that indicated by the official used car price index. The real cost of a used car actually was lower in 1980 than in 1977, and the same was true for the average transaction cost of new cars and for the list price index used in this study. However, from 1980 to 1983, the real cost of new and used cars increased sharply. For used cars, the average financing period increased by 22%, from 31 months in 1977 to 38 months in 1983.

Obviously, households living below the poverty line of $10,000 (in 1983 dollars) do not purchase new cars, nor do they have the opportunity to affect the characteristics of the fleet by ordering or selecting options on the cars they purchase. The fact that prices of used cars rose more rapidly than the transaction prices of new cars implies that poor households suffered relatively more than households purchasing new cars. Because black and Hispanic households are more often poor, they obviously suffered relatively greater losses than whites from reduced vehicle affordability and limited selection of options in a vehicle.

Specifically, unlike new car buyers at the top of the income scale, used car buyers at the bottom of the scale received a smaller percentage increase in fuel economy (possibly even a decline, given the vehicles they could afford) while suffering a higher percentage increase in the cost of the vehicles they purchased. From 1977 to 1983, the number of cars over 16 years old increased by 188% (Ref. 16, 1978 and 1984). Given their age, such cars in 1983 were not more fuel-efficient than those in this category in 1977. Although we have no data for prices of cars over 16 years old, the dramatic increase in demand for such vehicles, combined with a restricted supply, obviously implies a sharper percentage increase in price for this category of vehicle than for any other.

It is reasonable to infer that the poorest households were faced with the greatest percentage increase in vehicle cost with the least percentage gain in fuel efficiency. Consequently, it can be predicted that the 1977-83 market responses to the gasoline price increase of 1978-80 caused a far greater sacrifice of vehicle use by poor households than by other households.

At least some of the poverty-level households should have been tempted by the price increases to switch to public transit. Although there was a 65% real increase in state and local subsidies of transit operating expenses between 1977 and 1983, the BLS price deflators for local transit and commuter railroads indicate real price increases of about 10%.[6] The increased subsidies more than offset the 6% real drop in the small share of operating expenses paid by the federal government but may not have offset rising labor and fuels costs. Fuel costs for buses, which are almost exclusively diesel-fueled, rose more rapidly than for cars. The real CPI-deflated increase in gasoline prices from 1978 to 1983 was 29% and the increase for diesel fuel was 43.4%, based on the 1978-85 refiner-to-end-user series on finished motor gasoline and No. 2 fuel oil (Ref. 3, Aug. 1986). These price rises are higher than those for gasoline at retail stations, but they may well reflect costs to transit operators, who probably purchase wholesale. Further, although automobiles reduced their Btu-per-vehicle use by 15.8% for this period, the Btu-per-vehicle use by buses remained virtually unchanged.[19] Consequently, the real average cents-per-mile fuel cost for cars in fleets purchasing gasoline wholesale increased by about 8.6% from 1978 to 1983, while that for transit buses increased by 43.4%. This helps explain the increase that occurred in the BLS transit price deflator in spite of increased transit operating subsidies.

The federal government attempted to force technological improvement in automobiles through the CAFE standards, but it did not promote the introduction of more efficient technologies for buses. Technological improvements in the fuel efficiency of automobiles, whether forced by government or by the market, actually reduced the real cents-per-mile fuel costs of the average passenger car between 1977 and 1983. In contrast, the BLS transit and commuter railroad price series imply that the out-of-pocket costs for public transportation increased. Because the key criterion for auto use once the commitment to an automobile has been made is out-of-pocket fuel cost, substituting passenger car use for transit bus use in 1983 would make sense, and this should be more likely in areas where fuel costs per trip are higher, i.e., where average trips are longer.

The geographic pattern of switching between transit and automobiles is consistent with this logic. The substitution opportunities offered by transit were only used in central cities of standard metropolitan statistical areas (SMSAs), where typical trips are short. There, the average share of trips made by transit increased from 4.7% in 1977 to 5.4% in 1983. In suburban and rural areas, the rate of use of transit dropped (Ref. 17, p. 6-13).

In addition to these geographic substitution effects, a pattern of substitution by income can also be inferred. The average age of vehicles owned by households declines as income increases. The standard means of improving the fuel economy of a household's vehicles is to replace an existing vehicle with a more efficient one. From 1977 to 1983, if a household replaced a typical older car with a typical newer car (1974 or later model year), the fuel economy of the new vehicle was better. However, given that fleet fuel economy declined steadily from 1964 through 1973 (Ref. 13, Table 27), the younger the typical car of this period, the worse was its fuel economy. Thus, in 1983, if a household replaced a car 10 or more years old with a younger car still more than 10 years old, the household would typically have suffered a decline in fuel economy. According to our NPTS sample, the average age of vehicles held in 1983 by all households with less than $10,000 (1983) annual income was 9.7 years, but it was 9.5 years for white households, 10.3 for black, and 10.7 years for Hispanic.

If one assumes that fuel economy did not change for households that replaced a vehicle, then their out-of-pocket operating cost would increase in direct proportion to the increase in gasoline cost. Using retail prices of leaded fuel, this would translate into an effective real cents-per-mile fuel cost increase of 11.6% between 1977 and 1983 (Ref. 3, Aug. 1986), versus an increase of 9.8% for local transit and 8.8% for commuter rail and a decrease of 3.1% for taxis, using the BLS PCE price deflators.[6]

Given these relative out-of-pocket costs for low-income households and knowing that the demand for used cars increased most rapidly from 1977 to 1983, we can predict that these households would shift away from automobile use and toward public transportation. This is what happened according to the NPTS samples (Table 2). For all households with less than $10,000 of income, the estimated share of trips by taxi, local transit, and commuter rail rose from 4.8% of all trips (9.0% of trips made by private vehicle, taxi, local transit and commuter rail) in 1977 to 5.5% (13.0%) in 1983. This total is misleading, however, because it is dominated by compositional shifts of blacks and Hispanics. The comparable estimated percentages for whites were 2.8% (5.2%) in 1977 and 2.5% (5.3%) in 1983, a very small shift. The estimates indicate that low-income black households increased taxi, transit, and commuter rail use from 9.7% (19.5%) of all trips in 1977 to 12.7% (41.3%) in 1983, while Hispanics increased from 7.0% (13.0%) to 9.0% (21.3%).

If a high-income household replaced a typical 1977 passenger car with a new 1983 model, per-mile fuel use would decline by 29%. The corresponding figure for 1982 vs. 1976 is 35%; for 1981 vs. 1975, 39%; and for 1980 vs. 1974, 42%. The real increase in retail cost of unleaded fuel from 1977 to 1983 was 15%. Using the conservative assumption that high-income households realized a net improvement of about 25% in the fuel consumption rate of their vehicles from 1977 to 1983, the net reduction in cents-per-mile cost would be about 14%. Clearly, on the basis of out-of-pocket costs, high-income households would have used private vehicles rather than public transportation. With the exception of black households, this is what our NPTS estimates indicate.

Even though the number of 0- to 4-year-old cars and trucks dropped sharply from 1977 to 1983, the higher number of used vehicles caused the total number of vehicles in use to rise more rapidly than the driving-age (above 18) population and the number of registered drivers. Yet individual vehicles were not driven as many miles in 1983 as in 1977, with the result that the Federal Highway Administration estimates of car and truck VMT per driving-age person or per registered driver were nearly the same for these years. This probably represents a sacrifice in terms of consumer expectations, because VMT per registered driver had been increasing at an average annual rate of 1% between 1970 and 1977.

It is likely that a reliability trade-off was involved in this pattern of behavior. Because used cars are less reliable, it was probably necessary to keep more cars in use to allow the same amount of VMT per driver. It is also likely that the sharp increase in used car prices resulted from the efforts of former new-car buyers to save on the cost of vehicles so that the same amount of VMT could be enjoyed in spite of higher gasoline costs. This hypothesis is supported by the fact that the share of total personal consumption devoted to user-operated transportation declined from 14.7% in 1977 to 13.0% in 1983. During the same time, the share of user-operated transportation spending devoted to gasoline increased from 25% to 31% (Ref. 14, first quarter, 1986). Given the steady VMT and the drop in new car purchases, it is obvious that consumers generally substituted older, cheaper cars for those they had previously purchased and continued to drive about the same number of miles. In economic terms, the demand for total vehicles and VMT was very inelastic, but the demand for new vehicles was very elastic.

An important question is whether or not the strategy of households trying to adapt to rising gasoline prices succeeded. Higher-income consumers shifted their purchases from newer to older, cheaper vehicles, driving up the cost of used cars. The "trickle-down" effects forced the lowest-income households to attempt to substitute transit services for private autos. Given the geographic distribution of the best transit services, i.e., in urban areas and in central cities of SMSAs, one might anticipate increasing tendency for the poorest households to move to urban areas and central cities in the event of a gasoline price increase. However, the trend of job movement away from central cities and into the suburbs is well established. If the poorest households were to move closer to transit because of its lower cost as the number of jobs accessible by transit was decreasing, the ability of the poor to reach low-paying jobs might actually diminish as a result of this apparently logical decision.

The 1977-83 NPTS statistics are consistent with this pattern of change. Transit use increased in central cities at the same time it was decreasing in suburbs and rural areas. Distance to transit was decreased on the average by all household types, but far more dramatically for those households earning less than $10,000 (in 1983 dollars), and among those households it decreased most dramatically for minorities (Table 3). The same pattern was exhibited by the proportion living within two miles of transit. The NPTSs indicate reductions in distance to transit for all classes of household, but these reductions were only within urban areas (Table 3). In rural areas, distance increased for Hispanics and blacks, as it did for whites. Outside SMSAs, the proportion of transit trips decreased by 50%, from a minuscule 0.008 to 0.004. The NPTS sample distributions indicate that the proportion of minorities living in urban areas increased from 1977 to 1983, while the proportion of whites decreased slightly.

2.4 IMPLICATIONS OF 1977-83 ADAPTATIONS FOR MODELING TRANSPORTATION FUEL EXPENDITURES

The primary objective of this project has been to create an ability to estimate transportation fuel expenditure patterns for minority and majority populations in response to transportation fuel price changes. Section 2.3 shows that, while there is a great deal in common between the adaptation strategies of minorities and whites, there are also important differences. Although much of the adaptive behavior can be explained by standard economic theory, the NPTS data clearly indicate that low-income minorities reacted more strongly to fuel and vehicle price changes than did whites. Specifically, low-income minorities reduced private vehicle use and shifted to public transportation to a far greater degree than did low-income whites; in standard economic language, the elasticity of their response to fuel price increases was greater than that of whites.

Because of the sharp reduction in the use of private vehicles by low-income minority households from 1977 to 1983, a superficial analysis of fuel expenditures might conclude that, because of a very elastic response, the minority fuel expenditure share does not increase much in response to fuel price increases and that minorities adapt about as successfully to increases as do whites. However, because minorities substitute public transportation for the private vehicle to a much greater degree, a more accurate measure of the cost of their response is obtained by examining the total costs of making trips before and after the price increase. Such an estimate would include costs of public transportation, which therefore have been incorporated into MITRAM. Admittedly, the measures created are not measures of economic well-being, because they do not examine cost per trip and do not properly separate and account for all capital and operating costs. Nevertheless, given the importance of public transportation to minorities, the use of the out-of-pocket concept in MITRAM is more informative about household adaptation than is spending on fuel alone.

TABLE 3 NPTS Estimates of Distance to Transit (blocks)

	Income (1983 $, thousands)				
Groups	<10	10-24.9	>25	All Urban	All Rural
All groups					
1977	15.5	15.6	15.5	11.0	25.2
1983	12.8	14.6	15.0	8.4	26.3
% change	-17	-6	-3	-23	+4
White					
1977	16.6	16.7	16.3	11.9	25.3
1983	14.9	15.6	15.7	9.1	26.3
% change	-10	-6	-4	-24	+4
Black					
1977	12.9	10.7	7.8	6.6	25.3
1983	8.2	8.6	10.2	5.2	26.0
% change	-36	-20	+31	-21	+3
Hispanic					
1977	12.6	10.5	9.8	7.8	25.0
1983	7.6	11.4	9.2	6.7	26.5
% change	-40	+9	-7	-14	+6
All Urban					
1977	9.2	10.2	12.3		
1983	6.0	8.3	9.7		
% change	-34	-19	-21		
All Rural					
1977	25.1	25.6	24.8		
1983	25.2	26.5	26.8		
% change	+1	+3	+8		

3 PRIOR MODELS

In this section, we summarize a number of statistically based models from the literature for (1) vehicle holdings, (2) vehicle use (miles of travel), (3) gasoline demand (which can be derived from vehicle use and vehicle efficiency), (4) vehicle fuel economy, and (5) vehicle scrappage. The primary source of this information was Richardson's series of reports.[20-23] A more recent Argonne report sponsored by the Office of Minority Economic Impact is also cited.[24] A number of later survey publications by Richardson, which do not include the amount of statistical information used to construct the tables in this section, have not been cited, nor have many recent publications from the literature which address the effects of public transportation on automobile use.

3.1 VEHICLE OWNERSHIP AND USE

Eleven vehicle ownership models are detailed in Table 4. A measure of income is included as an independent variable in each model. A measure of operating cost influenced only by gasoline price is included in three models (#1, 8, and 11), and a variable measuring the effects of public transportation in two (#5 and 9). In both of the latter, transit use reduces the number of vehicles held. Three models include a direct measure of employment effects, and five include a variable that measures vehicle cost effects. Tests for each of these effects are presented in Sec. 4. Model #4 estimates that black households are significantly less likely to own cars than are all other households. That model,[24] using Residential Energy Consumption Survey Household Transportation Panel (RECS-TP) data collected from June 1979 to September 1981,[25] indicated that households headed by blacks, poor households (income <125% of poverty level), elderly-headed households, and female-headed households owned significantly fewer vehicles. It also indicated a small but significant drop in vehicle ownership rates during the months before and during the decline into the 1980 recession as compared to the recovery period.

Thirteen models for VMT are detailed in Table 5. Only four of the 13 (#4, 6, 7, and 10) estimate VMT per car, as done in this study; four estimate VMT per capita (#1, 5, 9, and 11), and five estimate VMT per household (#2, 4, 5, 12, and 13). A measure of income is included in 11 of these models (all but #7 and 13) and in the stock VMT equation in this report. The majority include a formulation accounting for operating cost (gasoline cost per gallon divided by vehicle-miles per gallon), as do both the stock and flow VMT equations in this report. None of the models, with the possible exception of Sweeney's, appear to directly estimate an effect for the purchase cost of the vehicle. In both VMT equations in this report, a measure of used car costs proved to provide significant explanatory power. Model #13 also examined the direct effects of used car cost on used car ownership and indirect effects on VMT per household. Model #5 indicated that, although households headed by blacks drove significantly less VMT per household, it was due to a lower rate of car ownership. In a model not presented in Table 4, black households were estimated to drive the cars that they owned 7% more than the base household in the sample.

3.2 GASOLINE DEMAND

Fifteen gasoline demand models are presented in Table 6. In MITRAM, gasoline demand is not estimated separately but is computed on the basis of estimates of vehicles held, VMT per vehicle, and on-road fuel efficiency per vehicle. Thus, all of the variables determining these three attributes are also determinants of gasoline demand. All of the models except #11, 14, and 15 estimate gasoline demand as a function of an income variable and all except #7, 14, and 15 use gasoline price; model #7 does not estimate a gasoline price effect. Two models (#14 and 15) use the indirect approach of including gasoline price or operating cost as a determinant of VMT, as do our VMT equations (see Sec. 4). Model #13 includes an estimate of the degree to which travel to work by transit reduces gasoline use, and another (#12) estimates an effect of the cost of train travel on gasoline use.

3.3 FUEL ECONOMY

Four models (#1, 4, 7, and 8) in Table 7 estimate average fleet fuel economy. Two of the four (#1 and 8) estimate current fuel economy as a function of current gasoline cost, with no allowance for lagged introduction of new car fuel economy into the fleet. The Sweeney model (#7) ages new cars into the fleet, applying factors for "death" and reduced use of cars as they age. The equation used in the current version of MITRAM also accounts for the delayed effect on fleet fuel economy of new car fuel economy. Two models (#6 and 7) estimate new car fuel economy. Both show a short-term increase in fuel economy one year after a gasoline price increase. MITRAM also shows such a short-term reaction and a much longer lagged reaction to sustained real gasoline price increases. A cross-sectional study (model #4) over a 28-month period indicated that the in-use fuel economy experienced by households headed by blacks was 8.6% lower than the base case, even after accounting for poverty.[24]

3.4 SCRAPPAGE

Table 7 includes two scrappage models (#2 and 5). The first indicates that scrapping drops when car prices rise or when unemployment is high, similar to results from one of the scrappage equations to be presented in Sec. 4. The second simply estimates probability of scrapping as a function of the age of the car.

TABLE 4 Vehicle Ownership Models

Source	Equations[a]
1 S.U.R.E. Demand Model of Automobile Size Choice Sponsor: Louisiana State University Author: Rodney L. Carlson Year: 1978 Type: Time Series (TS)	D(S) = - 0.267 P(S) + 0.755 YDC + 0.154 PG - 0.044 D74 D(C) = - 0.677 P(C) + 0.881 YDC + 0.699 PG - 0.671 SC - 0.213 D74 D(I) = - 0.377 P(I) + 0.502 YDC - 0.551 PG - 0.318 D74 - 0.213 DUAW D(F) = - 0.422 P(F) + 0.410 ICS - 0.418 PG - 0.12 D74 - 0.101 DUAW D(L) = - 0.307 P(L) + 0.741 YDC - 0.36 RPG + 0.405 SL - 0.177 D74 D(x) = Demand for car type x: S = subcompact, C = compact, I = intermediate, F = full size, L = luxury P(x) = Price of car type x YDC = Real income per capita PG = Price of gasoline RPG = Real price of gasoline Sx = Stock per capita of car type x D74 = Dummy for 1974 oil shortage DUAW = Dummy for UAW's 1970 strike ICS = Index of consumer sentiment, published by Univ. Michigan Survey Research Center
2 Fleet Model Sponsor: U.S. Dept. of Transportation, Transportation Systems Center Author: Environmental Impact Center, Inc. Year: 1976 Type: TS	$TC = -10.8 + 0.667\ TC_{-1} + 0.016\ YD + 0.473\ HH$ TC = Total cars (millions) YD = Disposable income (billions, 1967$) (t=2.4) HH = Households (millions) (t=2.7) t-values: TC_{-1}=7.4, intercept t=-2.3

[a] x_{-1} = one-year lagged value of variable x.

TABLE 4 (Cont'd)

	Source	Equations
3	Automobile Sector Forecasting Model Sponsor: Federal Energy Admin. Author: Jack Faucett Assoc. Year: 1977 Type: Cross-sectional (CS)	log(CPH) = -1.7481 + 0.4743 log(Ymb) CPH = Cars per household (HH) for the income group Ymb = Midpoint of income bracket
4	Demographic Influences on Household Travel and Fuel Purchase Behavior Sponsor: U.S. Dept. of Energy Authors: Y. Gur, M. Millar, and R. Morrison Year: 1986 Type: CS	VH = 1.755 - 0.18 BLK - 0.039 OTR - 0.227 POOR - 0.298 OLD + 0.195 SUBR + 0.24 RURAL - 0.039 WNTR - 0.02 SUMR + 0.154 SHORTAGE - 0.451 FEM - 0.64 P060979 - 0.043 P101279 - 0.052 P010380 - 0.025 P040680 VH = Vehicles per HH for vehicle-owning HH BLK = HH head is black (Standard error=0.024) OTR = HH head is nonwhite and nonblack (SE=0.053) POOR = HH income <125% of poverty level (SE=0.02) OLD = HH head is >64 years old (SE=0.013) SUBR = HH in an SMSA suburb (SE=0.015) RURAL = HH in rural area (SE=0.015) WNTR = Dec through Feb (SE=0.016) SUMR = June through Aug (SE=0.014) SHORTAGE = June-July 1979 (SE=0.078) FEM = Female HH head (SE=0.015) PM1M2YY = Period of months M1 through M2 in year YY (SE: P060979=0.018, P101279=0.02, P010380=0.021, and P040680=0.019)

TABLE 4 (Cont'd)

Source	Equations
5 Wharton EFA Motor Vehicle Demand Model, MARK I Sponsor: U.S. Dept. of Transportation, Transportation Systems Center Authors: Colin J. Loxley, Tim Osiecki, Kate Rodenrys, and Sheela Thanawala Year: 1978 Type: Mixed (TS,CS)	$\ln(Car) = -1.91069 + 0.563472 \ln(YD4) - 0.101018 \ln(FY15) - 0.199696 \ln(CCPM) - 0.0536255 \ln(NAC) + 0.0990298\ FSMSA + 0.421331 \ln(DRV)$ Car = Autos per family YD4 = Moving average (4-yr), real disposable family income FY15 = Fraction of families with income ≥ $15,000 CCPM = Capitalized cost per mile of purchase and operation NAC = Non-auto commuters per family FSMSA = Fraction of population in SMSAs DRV = Licensed drivers per family
6 Wharton EFA Motor Vehicle Demand Model, MARK II Sponsor: U.S. Dept. of Transportation, Transportation Systems Center Authors: Colin Loxley, Tim Osiecki, and Kate Rodenrys Year: 1978 Type: Mixed (TS,CS)	$\ln(CPDRV) = -3.7628 + 0.646989 \ln(YPD4) - 0.385023 \ln(CCPM) + 0.281795\ FHHSub - 0.382618 \ln(PY15\ 75)$ CPDRV = Cars per driver YPD4 = Four-year moving average of real total personal income less taxes and transfers per driver CCPM = Capitalized cost per mile per car FHHSub = Fraction of HH in suburbs of SMSAs (SubHH/THH) PY15 75 = Percent families with income ≥ $15,000 in 1975
7 Automobile Simulation Model of Project Independence Evaluation System (PIES) Sponsor: Federal Energy Admin. Author: James Sweeney Year: 1975 (later revised, see #8) Type: Mixed (TS,CS)	$NCS = POP \exp[4.0792 - 3.7554 \log(OS_{-1}/POP_{-1}) + 2.3155 \log(\overline{VMTC}) + 1.778 \log(\overline{YDC58}) - 0.078164\ RU]$ NCS = New car sales (thousands) POP = Total population (millions) OS_{-1} = Lagged age-adjusted stock of cars (t=-6.2754) $\overline{VMTC}$ = VMT per capita (t=2.4835) YDC58 = Real disposable income per capita (thousands, 1958$) (t=1.9503) RU = Unemployment rate (t=-3.6297) Intercept t=0.6564 --------

TABLE 4 (Cont'd)

Source	Equations
8 Passenger Car Gasoline Demand Model Sponsor: U.S. Dept. of Energy Author: James L. Sweeney Year: 1979 Type: Unknown	$\log(NCPC) = 16.993 - 3.022 \log(SLOPC) + 2.325 \log(YDC) - 0.479 \log(PG) - 0.786 \log(CSTK) + 0.049\ RU$ NCPC = New car registration per capita SLOPC = Stock left over from prior vintages per capita YDC = Real disposable income per capita PG = Real price of gasoline CSTK = Passenger car stock RU = Unemployment rate
9 Vehicle Quantity Submodel Author: Kenneth Train, Cambridge Systematics Year: 1980 Type: CS	$Pi = \exp(Vi)/[\exp(V1) + \exp(V2) + 1]$ Pi = Probability of having i vehicles in the HH (i=1,2 and P0=1-P1-P2) Vi = Sum of factors reflecting HH desire and willingness to own i vehicles $V1 = 1.05 \log(YH) + 1.08\ WH + 0.181 \log(SH) - 0.0009\ ATC + 0.635\ AU - 1.79$ YH = HH income (t=3.69) WH = HH workers (t=3.78) SH = HH size (t=0.43) ATC = Annual transit trips per capita in HH area of residence (t=1.82) AU = Average utility in class/vintage choice (t=7.14) Intercept t=2.97 $V2 = 1.57 \log(YH) + 1.50\ WH + 0.197 \log(SH) - 0.0021\ ATC + 0.635\ AU - 4.95$ t-values: YH=3.52, WH=4.78, SH=0.39, ATC=3.42, AU=7.14, intercept=5.19

TABLE 4 (Cont'd)

	Source	Equations
10	Econometric Model of Consumer Demand for New and Replacement Automobiles Sponsor: Data Resources Inc. Authors: Philip K. Verleger and James Osten Year: 1976 Type: Unknown	$\ln(CC) = -5.602 - 0.132 \ln(CAS) + 0.818 \ln(DRVC) + 0.408 \ln(YP) + 0.062 \ln(VMTC/VMTC_{-1})$ CC = Cars per capita CAS = Cost of auto stock (includes depreciation, first-year operating cost, and interest cost of a new car) DRVC = Drivers per capita YP = Permanent income VMTC = Vehicle-miles of travel per capita
11	New Car Sales/Auto Ownership/Vehicle Miles Traveled (NAV) Model Sponsor: Research Applied to National Needs (NSF research) Authors: S. Wildhorn, B.K. Burright, J.H. Enns, and T.F. Kirkwood, (Rand Corporation) Year: 1974 Type: TS (1954-1972)	$IUP = -0.896 + 1.7268\ IPN - 0.87122\ IPG + 0.44809\ Y - 1.404\ AH_{-1} - 0.029592\ DUAW$ IUP = Index of real used car prices (IUP>0) IPN = Index of real new car prices IPG = Index of real gasoline prices Y = Permanent income per HH AH_{-1} = Last year's autos held this year DUAW = Dummy for auto manufacturing strike -------- $NAH = -0.5080 - 0.20869\ IPN + 0.7305\ Y/Y_{-1} + 0.01733\ DUAW$ NAH = New car sales per HH -------- $UAH = -0.05894 - 0.26645\ IUP + 0.63665\ IPN - 0.59339\ IPG + 0.22529\ Y - 0.01186\ DUAW$ UAH = Used cars per HH

Source: Refs. 20-24.

TABLE 5 Vehicle-Mile Models

	Source	Equations[a]
1	Components of Short-Run Demand for Gasoline Model Sponsor: Wayne State University Author: Carol A. Dahl Year: 1979 Type: Time Series (TS)	log(VMTC) = −4.54 − 0.101[log(PG)/log(MPG)] + 0.147 log(YDC) + 1.071 log(APC) VMTC = VMT per capita PG = Price of gasoline (1958$/gallon) MPG = Miles per gallon for autos YDC = Disposable income per capita (thousands, 1958$) APC = Stock of autos per capita (thousands)
2	Economics Submodel of EEA Gasoline Consumption Model Sponsor: Federal Energy Admin. Author: Energy and Environmental Analysis, Inc. Year: 1975 Type: TS	MH = 1.21 + 0.21 RU + 0.0016 YDH − 25.9 PG/(CPI•MPG) MH = VMT per household (HH) RU = Unemployment rate (t=4.4) YDH = Real disposable income per HH (t=30.2) PG/(CPI•MPG) = Gasoline cost per mile (1967$) (t=2.2)
3	Vehicle Miles Traveled Model Sponsor: U.S. Dept. of Transportation, Transportation Systems Center Author: Environmental Impact Center, Inc. Year: 1976 Type: TS	VMT = VMT_{-1} + DVMT DVMT = 11.293 DHH + 0.857 DYD − 8273 DCPM − 45 DPT VMT = Vehicle-miles of travel (billions) DVMT = One year change in VMT (billions) DHH = Change in HH (millions) (t=3.2) DYD = Change in disposable income (billions, 1967$) (t=4.8) DCPM = Gas cost per mile (1967$) (t=−5.2) DPT = Change in transit supply (billions of vehicle-miles) (t=−1.4)

[a] x_{-1} = one-year lagged value of variable x.

TABLE 5 (Cont'd)

Source	Equations
4 Automobile Sector Forecasting Model Sponsor: Federal Energy Admin. Author: Jack Faucett Assoc. Year: 1977 Type: Cross-sectional (CS)	$\text{HHVMT} = -52979.8 + 15087 \log(\text{YD}) + 6337.7\ \text{ACO} - 2204.24 \log(100\ \text{IGC})$ YD = Average HH disposable income ACO = Average HH auto ownership IGC = Index of gasoline cost (1967 = 1.00) -------- $\text{AVMT}(y) = 17.9729 - 9.57841 \log(y)$ AVMT(y) = Annual VMT for car of age y (thousands)
5 Demographic Influences on Household Travel and Fuel Purchase Behavior Sponsor: U.S. Dept. of Energy Authors: Y. Gur, M. Millar, and R. Morrison Year: 1986 Type: CS	$\text{MMH} = 1399.9 - 61.1\ \text{BLK} - 219.9\ \text{POOR} - 627.1\ \text{OLD} + 276.6\ \text{SUBR} + 327.2\ \text{RURAL} - 91.7\ \text{WNTR} + 107.6\ \text{SUMR} + 309.1\ \text{SUPPLY} - 414.4\ \text{FEM} - 98.2\ \text{P060979} - 104.9\ \text{P010380} - 106.9\ \text{P040680} - 56.7\ \text{P070980} - 113.4\ \text{P010381} - 54.9\ \text{P040681}$ MMH = Monthly VMT by vehicle-owning HH BLK = HH head is black (Standard error=31.3) POOR = HH income <125% of poverty level (SE=25.9) OLD = HH head is >64 years old (SE=17.4) SUBR = HH in an SMSA suburb (SE=19.3) RURAL = HH in rural area (SE=20) WNTR = Dec through Feb (SE=23.6) SUMR = June through Aug (SE=19.3) SUPPLY = Problems with fuel supply reported by HH (SE=102.3) FEM = Female HH head (SE=20.3) PM1M2YY = Period of months M1 through M2 in year YY (SE: P060979=26.5, P010380=28.8, P040680=27.1, P070980=28.1, P010381=28.6, and P040681=26.9) --------

TABLE 5 (Cont'd)

Source	Equations
5 (Cont'd)	$MMVH = 768.2 + 57.3\ BLK - 44.9\ POOR - 261.7\ OLD + 77.6\ SUBR + 86.6\ RURAL - 47.0\ WNTR + 70.5\ SUMR - 51.1\ FEM$ MMVH = Monthly miles per vehicle for vehicle-owning HH SE: BLK=15.7, POOR=13.3, OLD=8.4, SUBR=9.1, RURAL=9.4, WNTR=9.0, SUMR=7.9, FEM=10.5
6 Wharton EFA Motor Vehicle Demand Model, MARK I Sponsor: U.S. Dept. of Transportation, Transportation Systems Center Authors: Colin J. Loxley, Tim Osiecki, Kate Rodenrys, and Sheela Thanawala Year: 1978 Type: Mixed (TS,CS)	$VMTU = -1.43792 - 0.371407 \ln[(PG/CMPG)/(CPI/125.3)] + 0.298117 \ln(PSMSA \bullet DRV/CSTK) + 0.61974 \ln[0.25\ YDC + 0.5\ YDC_{-1} + 0.25\ YDC_{-2}]$ VMTU = Urban VMT per car (mid-year) PG = Price of gasoline ($/gallon) CMPG = City mpg for the fleet CPI = Consumer price index (1967=100) PSMSA = Percent population in SMSAs DRV = Licensed drivers CSTK = Mid-year stock of cars YDC = Real disposable income per capita, less taxes and certain transfer payments
7 Automobile Fleet Fuel Efficiency Forecasting Sponsors: Purdue University, Indiana State Highway Comm. Authors: Fred L. Mannering and Kumares C. Sinha Year: 1979 Type: CS	$RVMT = 1.8535 - 0.4813 \ln(AG + 1)$ RVMT = Relative rate of VMT for a car of given age AG = Age group (AG=1 for age <2, AG=2 for age 2-3, AG=3 for age 3-4)

TABLE 5 (Cont'd)

	Source	Equations
8	Automobile Simulation Model of Project Independence Evaluation System (PIES) Sponsor: Federal Energy Admin. Author: James Sweeney Year: 1975 Type: Mixed (later revised, see #9)	$VMTC = \exp\{0.80967 \log(VMTC_{-1}) + 6.5184 - 0.35775 \log(CPM) + 0.97561 \log(YDC58) + 0.0026184\ RU - 0.80967\ [6.5184 - 0.35775 \log(CPM_{-1}) + 0.97561 \log(YDC58_{-1}) + 0.0026184\ RU_{-1}]\}$ VMTC = VMT per capita CPM = Auto cost per mile (t=-1.785) YDC58 = Disposable income per capita (thousands, 1958$) (t=11.1515) RU = Unemployment rate (t=0.9352) t-values: $VMTC_{-1}$=12.683, intercept t=12.1275
9	Passenger Car Gasoline Demand Model Sponsor: U.S. Dept. of Energy Author: James L. Sweeney Year: 1979 Type: Unknown	$\log(VMTC) = 2.381 - 0.295 \log(GCPM) + 0.299 \log(YDC) - 1.54 \log(WHP) + 0.519 \log(CSTKPC) - 0.006 \log(DHIST) - 0.004 \log(DUM74)$ VMTC = VMT per capita GCPM = Gasoline cost per mile YDC = Disposable income per capita WHP = Weekly hours of production on private nonagricultural payrolls CSTKPC = Total cars per capita DHIST = Dummy to account for changes in historical data series DUM74 = Dummy for the year 1974

TABLE 5 (Cont'd)

Source	Equations
10 Vehicle Quantity Submodel Author: Kenneth Train, Cambridge Systematics Year: 1980 Type: CS	$\log(VMT1) = 0.1406 \log(YH) - 0.2795\ OCPM + 0.2131 \log(SH) + 0.17777\ WH - 0.000258\ ATC + 0.1163\ DGMM + 0.0477\ DLMM - 0.179\ NE - 0.074\ MW - 0.167\ S + 8.709$ VMT1 = Annual VMT for one-vehicle HH YH = HH income (t=1.49) OCPM = Operating cost (¢ per mile) (t=2.63) SH = HH size (t=1.71) WH = HH workers (t=1.61) ATC = Annual transit trip per capita in the HH area of residence (t=0.78) DGMM = Dummy for residence in an SMSA with over 1 million population (t=0.377) DLMM = Dummy for residence in an SMSA with less than 1 million population (t=0.283) NE = Dummy for northeast USA (t=0.93) MW = Dummy for midwest USA (t=0.4) S = Dummy for south USA (t=0.89) Intercept t=15.5 -------- $\log(VMT2) = 0.276 \log(YH) + 0.432\ DNV - 0.0351\ OCPM + 0.08331 \log(SH) + 0.0284\ WH - 0.000421\ ATC + 0.2\ DGMM - 0.092\ DLMM - 0.174\ NE - 0.107\ MW - 0.648\ S + 6.27$ VMT2 = VMT for each vehicle for 2-vehicle HH DNV = Dummy for newer of the two vehicles (t=5.16) t-values: YH=3.7, OCPM=0.472, SH=0.721, WH=0.456, ATC=2.2, DGMM=1.06, DLMM=0.876, NE=1.18, MW=0.93, S=0.541, intercept=15.8

TABLE 5 (Cont'd)

	Source	Equations
11	Econometric Model of Consumer Demand for New and Replacement Automobiles Sponsor: Data Resources Inc. Authors: Philip K. Verleger and James Osten Year: 1976 Type: Unknown	$\ln(VMTC) = 0.351 + 0.672 \ln(CC) + 0.464 \ln(YPD) - 0.187 \ln(VOCPM)$ VMTC = VMT per capita CC = Cars per capita YPD = Real personal disposable income VOCPM = Variable operating cost per mile for an average car
12	A Method for Projecting Aggregate Auto Miles Traveled Sponsor: U.S. Dept. of Transportation Authors: Donald E. Ward and Linda Horan Year: 1975 Type: TS	$MH = 1590 + 0.6233\ MH_{-1} + 2153\ DRV + 0.3936\ YDH58 - 140580\ (RPG/AMPG)$ MH = VMT per HH DRV = Drivers per HH (t=2.07) YDH58 = Disposable income per HH (1958$) (t=2.57) RPG/AMPG = Gasoline cost gas per mile (1967$) (t=-5.75) t-values: MH_{-1}=6.21, intercept t=1.06
13	New Car Sales/Auto Ownership/Vehicle Miles Traveled (NAV) Model Sponsor: Research Applied to National Needs (NSF research) Authors: S. Wildhorn, B.K. Burright, J.H. Enns, and T.F. Kirkwood (Rand Corporation) Year: 1974 Type: TS (1954-1972)	$\log(AMH) = 7.996 + 0.86405 \log(AH) - 0.44409 \log(IPG) + 0.44409 \log(MPG) + 0.03532\ DREG$ AMH = Annual auto miles per HH AH = Auto per HH = New car sales per HH (NAH) + Used cars per HH (UAH) (see Table 4, model #11) IPG = Index of real gasoline prices MPG = Average fuel efficiency of HH cars DREG = Dummy for federal regulations

Source: Refs. 20-24.

TABLE 6 Gasoline Demand and Price Models

Source	Equations[a]
1 Gasoline Demand Model Sponsor: U.S. Dept. of Transportation, Transportation Systems Center Author: David Anderson Year: 1974 Type: Mixed (CS,TS)	$QPC = 0.03064\ YDC - 131.5\ RPG + 0.824\ QPC_{-1} - 8.80\ AMPG + \Sigma(i=10 \text{ to } 58)\ bi$ QPC = Gasoline demand per capita YDC = Real disposable income per capita (t=11.68) RPG = Real gasoline price (t=-7.43) AMPG = Fleet fuel efficiency (t=-3.17) bi = State- or territory-specific intercept t-values: QPC_{-1}=41.6
2 Econometric Models of the Demand for Motor Fuel Sponsors: National Science Fndn., Federal Energy Admin. Author: Burke K. Burright and John H. Enns (RAND) Year: 1975 Type: TS	$\log(QPC) = -0.66 - 0.27 \log(RPG) + 0.18 \log(YDC) + 0.93 \log(VPC) - 0.09\ \%U$ QPC = Short-run demand of gas per capita RPG = Real price of regular gasoline (t=-11.5) YDC = Disposable income per capita (t=9.5) VPC = Registered vehicles per capita (millions) (t=42.3) %U = Percent population in urban areas (t=1.8) Intercept t=-3.5 -------- $\log(QPCA) = 8.337 - 0.19 \log(RPG) - 0.81 \log(AMPG) + 0.19 \log(W) + 0.01 \log(RU) + 0.849 \log(VPC) + 0.42\ DP68$ QPCA = Short-run demand for gasoline per capita (autos only) AMPG = Average auto fuel efficiency RU = Unemployment rate (%) DP68 = Dummy for post-1968

[a] x_{-1} = one-year lagged value of variable x.

TABLE 6 (Cont'd)

	Source	Equations
3	American, Canadian, and European Gasoline Consumption Model Sponsor: Wayne State University Author: Carol A. Dahl Year: 1978 Type: TS	Gasoline Consumption Short-run Elasticities Real gasoline price = -1.048 Real disposable income per capita = 0.322 Total vehicle per capita = 0.545 Population density = 0.134
4	Components of Short-Run Demand for Gasoline Model Sponsor: Wayne State University Author: Carol A. Dahl Year: 1979 Type: TS	$\log(QPC) = -4.109 + 0.442 \log(PG) + 0.322 \log(YDC) + 0.716 \log(APC)$ QPC = Gasoline demand per capita (thousands of gallons) PG = Price of gasoline (1958\$ per gallon) YDC = Disposable income per capita (thousands, 1958\$) APC = Stock of autos per capita (thousands)
5	Economics Submodel of EEA Gasoline Consumption Model Sponsor: Federal Energy Admin. Author: Energy and Environmental Analysis, Inc. Year: 1975 Type: TS	$Q = 28.5 - 118[PG/(CPI \cdot AMPG)] - 0.4\ RU - 19.6\ DYD - 10.5(NCP/UCP) + 3\ DVMT$ Q = Gasoline demand PG/(CPI•AMPG) = Real cost of gas per mile for the stock (t=2.5) RU = Unemployment rate (t=2.0) DYD = Change in real disposable income (t=2.4) NCP/UCP = New car price divided by used car price (t=5.9) DVMT = Change in VMT per car (t=3.6)

TABLE 6 (Cont'd)

Source	Equations
6 ORNL Highway Gasoline Demand Model Sponsor: U.S. Dept. of Energy Author: David L. Greene Year: 1978-80 Type: Unknown	QS = - 0.1396 PGw + 0.3564 YH - 0.04722 FPOP18 + 0.03991 SCar + 0.1556 LCar + 0.03025 LTrk - 0.04918 FSMSA - 0.04982 DEN - 0.7705 MPG + 0.5715 MC + StateC QS = Gasoline demand per household (HH) in a state PGw = Price of gasoline, leaded and unleaded, weighted by sales YH = HH income FPOP18 = Fraction of population under 18 SCar = Small cars per HH LCar = Large cars per HH LTrk = Light trucks per HH FSMSA = Fraction of population in SMSAs DEN = Population density MPG = Stock fuel efficiency MC = Maintenance cost (1967$) StateC = State-specific constant
7 Demographic Influences on Household Travel and Fuel Purchase Behavior Sponsor: U.S. Dept. of Energy Authors: Y. Gur, M. Millar, and R. Morrison Year: 1986 Type: CS	$FH = 124.19 + 4.84 BLK - 6.96 OTR - 12.23 POOR - 44.64 OLD + 18.03 SUBR + 21.78 RURAL - 4.24 WNTR + 5.53 SUMR + 21.52 SUPPLY - 36.28 FEM - 39.42 P060979 - 24.16 P101279 - 17.19 P010380 - 17.52 P040680 - 13.93 P070980 - 7.69 P101280 - 7.41 P010381 - 4.51 P040681 $FH = Monthly fuel expenditures per HH for vehicle-owning HH ($) BLK = HH head is black (Standard error=2.54) OTR = HH head is nonwhite and nonblack (SE=5.59) POOR = HH income <125% of poverty level (SE=2.10) OLD = HH head is >64 years old (SE=1.41) SUBR = HH in an SMSA suburb (SE=1.74) RURAL = HH in rural area (SE=1.62)

TABLE 6 (Cont'd)

	Source	Equations
7	(cont'd)	WNTR = Dec through Feb (SE=1.97) SUMR = June through Aug (SE=1.74) SUPPLY = Problems with fuel supply reported by HH (SE=8.29) FEM = Female HH head (SE=1.64) PM1M2YY = Period of months M1 through M2 in year YY (SE: P060979=2.47, P101279=2.95, P010380=2.16, P040680=2.68, P070980=2.62, P101280=2.94, P010381=3.15, P040681=2.67)
8	Demand Model for Gasoline and Residential Electricity Sponsor: Ford Foundation, Council on Environmental Quality Authors: H.S. Houthakker, P.K. Verleger, and D.P. Sheehan Year: 1974 Type: TS	$\ln(Qit) = 0.593 - 0.075 \ln(PGit) + 0.303 \ln(YDit) + 0.696 \ln(Qit_{-1})$ Qit = Individual gasoline demand in state i at time t PGit = Gasoline price in state i at time t YDit = Personal disposable income in state i at time t
9	World Demand for Gasoline Sponsor: Ohio State University, Hamilton College Authors: Rajindar K. Koshal and James Bradfield Year: 1975 Type: CS	$\log(Q) = Int + a \log(PG) + b \log(CQ) + c \log(YC)$ Q = Gasoline demand (gallons) Int = Intercept (-0.2154 for low-income countries, 0.8528 for high-income countries, and 0.866 for both) a = -0.9875 for low-income countries, -1.231 for high-income countries, and -1.116 for both PG = Gasoline price (U.S. cents) b = 0.8314 for low-income countries, 0.8817 for high-income countries, and 0.8625 for both CQ = Vehicle stock in car equivalent units c = 0.4875 for low-income countries, 0.331 for high-income countries, and 0.3107 for both YC = Income per capita (U.S. dollars)

TABLE 6 (Cont'd)

	Source	Equations
10	Temporal Cross-Section Specification of Regional Demand for Gasoline Sponsors: National Science Fndn., U.S. Dept. of Energy Authors: John Kraft and Mark Rodekohr Year: 1978 Type: (TS) (1954-1972 data)	$QPC = 1.63 - 0.18\ (PG/CPI) + 0.51\ YDC + 0.32\ STK_{-1}$ for Northeast QPC = Gasoline demand per capita PG = Retail gasoline price CPI = Consumer price index YDC = Per capita disposable income STK_{-1} = Lagged total auto registration per capita
11	Gasoline Use Model Sponsor: Research Applied to National Needs (NSF research) Author: Robert G. McGillivray Year: 1975 Type: TS (model does not fit 1973-1974 data)	$QPC = -111.68 - 1.79\ RPG + 818.69\ NCPC + 0.32\ AQC + 0.70\ QPC_{-1}$ QPC = Gasoline demand per capita RPG = Deflated price of gas (t=-2.99) NCPC = New car registration per capita (t=7.04) AQC = Average gas consumption per car (t=5.15) t-values: QPC_{-1}=12.73, intercept t=-2.99
12	An Analysis of the Private and Commercial Demand for Gasoline Sponsor: Michigan State University Author: J. Ramsey, R. Rasche, and B. Allen Year: 1974 Type: TS	$\log(QHH) = 2.047 - 0.222\ RPG + 0.177\ ITT - 4.034\ F1624 - 1.078/YDH$ QHH = Gasoline demand per HH RPG = Gasoline price/CPI (t=-1.82) ITT = Price index of train travel/CPI (t=1.49) F1624 = Proportion of population in the 16-24 age group (t=4.74) YDH = Real disposable income per HH (t=11.75) Intercept t-value not given

TABLE 6 (Cont'd)

Source	Equations
13 Urban Size Structure and Private Expenditures for Gasoline Sponsors: George Washington and George Mason Universities Authors: Charles T. Stewart and James T. Bennett Year: 1975 Type: CS	$QPC = 51.545 - 0.2036\ DP\% - 0.0117\ \%CCITY + 0.2278\ \%NW + 0.0033\ MEDY + 0.123\ \%POV + 16.0508\ W - 10.849\ NE + 9.7149\ NC + 0.0065\ MNFG + 5.3273\ DVRS - 0.027\ POP70 - 15.7417\ \%P16 + 0.0002\ CCDEN - 0.0008\ SUBDEN - 9.3278\ PORT + 0.0691\ HOTEL + 0.0063\ \%P65 + 0.2391\ PG - 0.1196\ \%WKPT$ QPC = Gasoline sales per capita DP% = Percent change in population 1960-70 (SE=0.0896) %CCITY = Percent SMSA population in central city (SE=0.0746) %NW = Percent SMSA population that is nonwhite (SE=0.1165) MEDY = Median family income (SE=0.002) %POV = Percent SMSA families below poverty line (SE=0.7108) W = West region dummy (SE=3.891) NE = Northeast region dummy (SE=5.4032) NC = North Central region dummy (SE=4.5612) MNFG = Manufacturing SMSA dummy (SE=3.1316) DVRS = Diversified manufacturing SMSA (SE=2.6693) POP70 = 1970 population (SE=0.001) %P16 = Percent SMSA population 16 or older (SE=16.54) CCDEN = Central city density (population per sq. mi) (SE=0.0004) SUBDEN = Density outside central city (population per sq. mi) (SE=0.0011) PORT = Sea/lake port dummy (SE=2.6279) HOTEL = Receipts of hotel, motel and tourist courts (1967$/capita) (SE=0.0131) %P65 = Percent SMSA population 65 and older (SE=0.0047) PG = Average gasoline price (SE=0.8942) %WKPT = Percent work trips by transit (SE=0.0363) Intercept SE=43.9841

TABLE 6 (Cont'd)

	Source	Equations
14	Econometric Model of Consumer Demand for New and Replacement Automobiles Sponsor: Data Resources Inc. Authors: Philip K. Verleger and James Osten Year: 1976 Type: Unknown	$\ln(Q) = 6.3765 + 0.813616\ [\ln(TVMT)/\Sigma(Wi \cdot Gi \cdot Ki)]$ Q = Quantity of gasoline demanded TVMT = Total VMT Wi = Normal usage of car vintage i Gi = Average mpg for car vintage i Ki = Stock of cars vintage i
15	New Car Sales/Auto Ownership/Vehicle Miles Traveled (NAV) Model Sponsor: Research Applied to National Needs (NSF research) Authors: S. Wildhorn, B.K. Burright, J.H. Enns, and T.F. Kirkwood (Rand Corporation) Year: 1974 Type: TS (1954-1972)	$\log(QHH) = \log(AMH) - \log(MPG)$ QHH = Gasoline demanded by a HH AMH = Annual auto miles per HH MPG = Average fuel efficiency of HH cars

Source: Refs. 20-24.

TABLE 7 Other Related Models

	Source	Equations[a]
1	Components of Short-Run Demand for Gasoline Model Sponsor: Wayne State University Author: Carol A. Dahl Year: 1979 Type: TS	log(MPG) = 2.714 + 0.212 log(PG) - 0.028 log(YDC) - 0.013 PDummy MPG = Average U.S. miles per gallon PG = Price of gasoline (1958$/gallon) YDC = Disposable income per capita (thousands, 1958$) PDummy = Pollution dummy set to zero for pre-1968 years
2	Automobile Sector Forecasting Model Sponsor: Federal Energy Admin. Author: Jack Faucett Assoc. Year: 1977 Type: CS	SCR(t) = 0.40675 - 0.078433 NCI(t) - 0.015519 RU(t) SCR = Scrappage rate of vehicles eight years and older NCI(t) = New car price index for year t (1967=1.00) RU(t) = Unemployment rate for year t
3	ORNL Highway Gasoline Demand Model Sponsor: U.S. Dept. of Energy Author: David L. Greene Year: 1978-80 Type: Unknown	A vehicle fuel efficiency model and a fuels technology model are included.

[a] x_{-1} = one-year lagged value of variable x.

TABLE 7 (Cont'd)

Source	Equations
4 Demographic Influences on Household Travel and Fuel Purchase Behavior Sponsor: U.S. Dept. of Energy Authors: Y. Gur, M. Millar, and R. Morrison Year: 1986 Type: CS	MPG = 14.53 - 1.25 BLK + 0.829 OTR -0.95 POOR - 0.75 OLD + 0.653 SUBR + 0.489 RURAL - 0.914 WNTR + 0.562 SUMR - 0.457 SHORTAGE + 0.705 FEM MPG = Average fuel efficiency of household (HH) vehicle BLK = HH head is black (Standard error=0.144) OTR = HH head is nonwhite and nonblack (SE=0.31) POOR = HH income <125% of poverty level (SE=0.132) OLD = HH head is >64 years old (SE=0.09) SUBR = HH in an SMSA suburb (SE=0.09) RURAL = HH in rural area (SE=0.092) WNTR = Dec through Feb (SE=0.088) SUMR = June through Aug (SE=0.081) SHORTAGE = June-July 1979 (SE=0.139) FEM = Female HH head (SE=0.107) -------- NFP = 4.965 + 0.584 BLK - 0.538 OTR + 0.199 POOR - 1.503 OLD - 0.415 RURAL - 0.251 WNTR + 0.235 SUMR - 0.29 FEM + 0.678 SUPPLY NFP = Monthly fuel purchases per vehicle SUPPLY = Problems with fuel supply reported by HH (SE=0.35) SE: BLK=0.142, OTR=0.226, POOR=0.13, OLD=0.127, RURAL=0.129, WNTR=0.157, SUMR=0.139, FEM=0.126 -------- %FU = 65.66 - 19.63 BLK + 10.73 OTR - 8.42 POOR + 14.15 OLD - 7.82 RURAL + 11.74 SHORTAGE + 4.02 SUPPLY - 5.42 FIRSTV %FU = Percent of fuel purchases that are complete fillups FIRSTV = Vehicle involved is listed as the first HH vehicle SE: BLK=1.7, OTR=2.54, POOR=1.5, OLD=1.45, RURAL=1.49, SHORTAGE=2.6, SUPPLY=3.85, FIRSTV=1.39

TABLE 7 (Cont'd)

	Source	Equations
4	(Cont'd)	AINV = 58.53 - 6.77 BLK + 5.35 OTR - 3.47 POOR + 8.51 OLD - 3.15 RURAL - 0.6 WNTR - 0.71 SUMR + 4.37 SHORTAGE + 1.89 FEM + 2.29 SUPPLY - 2.9 FIRSTV AINV = Average tank of fuel carried (%) SE: BLK=0.75, OTR=1.12, POOR=0.65, OLD=0.63, RURAL=0.64, WNTR=0.77, SUMR=0.73, SHORTAGE=1.23, FEM=0.62, SUPPLY=1.68, FIRSTV=0.6
5	Automobile Fleet Fuel Efficiency Forecasting Sponsor: Purdue University, Indiana State Highway Comm. Authors: Fred L. Mannering and Kumares C. Sinha Year: 1979 Type: CS	$P(S) = 0.02684 + 0.000127\ AGE^3$ P(S) = Probability of scrapping a car of given age AGE = Age of the car in years
6	Automobile Simulation Model of the Project Independence Evaluation System (PIES) Sponsor: Federal Energy Admin. Author: James Sweeney Year: 1975 Type: Mixed (later revised, see #7)	$NMPG = \exp[3.22175 + 0.68777 \log(RPG_{-1}/EFF) + \log(EFF)]$ NMPG = miles per gallon for new cars RPG_{-1} = Lagged gas price/CPI (t=7.5798) EFF = Measure of technical efficiency Intercept t=31.8728 -------- $QPM = (NCS/NMPG) + 0.93\ (0.92\ QPM_{-1})$ QPM = Fuel use per mile NCS = New car sales (see Table 4, model #7) NMPG = Miles per gallon for new cars

TABLE 7 (Cont'd)

Source	Equations
7 Passenger Car Gasoline Demand Model Sponsor: U.S. Dept. of Energy Author: James L. Sweeney Year: 1979 Type: Unknown	$AMPGt = ESt/\{\Sigma(i=t-15 \text{ to } t)\ [PCRi \cdot SUit \cdot RVMTit/MPGi] + ESOLD\}$ AMPGt = Average fuel efficiency of fleet at year t ESt = Effective stock of cars at t PCRi = New car registration of vintage i in year t SUit = Surviving fraction of cars of vintage i in year t RVMTit = Relative VMT (rate) of cars of vintage i in year t MPGi = Fuel efficiency of cars vintage i ESOLD = Sum of weighted 1/MPG of cars older than 15 years -------- $\log(NCMPG) = 3.344 + 0.721 \log(RPG_{-1}) + 0.279 \log(EFF)$ NCMPG = New car miles per gallon RPG_{-1} = Lagged real gas price (t=7.9) EFF = Technical efficiency of cars, equals one in 1974 (t not given) Intercept t=32.0
8 New Car Sales/Auto Ownership/ Vehicle Miles Traveled (NAV) Model Sponsor: Research Applied to National Needs (NSF research) Authors: S. Wildhorn, B.K. Burright, J.H.Enns, and T.F. Kirkwood (Rand Corporation) Year: 1974 Type: TS (1954-1972)	$\log(MPG) = 2.656 + 0.17015 \log(IPG) - 0.2228\ DREG$ MPG = Average fuel efficiency of HH cars IPG = Index of real gasoline prices DREG = Dummy variable for federal regulations

Source: Refs. 20-24.

4 ESTIMATION OF COEFFICIENTS

The theory of simultaneous equations estimation requires that unique "shifter" variables exist for each of the equations to obtain proper estimates. In this case, because both vehicle characteristics and public transportation are heavily influenced by government policy, appropriate shifter variables could be obtained from government policy records. Particularly, the degree of subsidy of transit could be used for public transportation, and environmental, safety, and fuel efficiency regulations could be used as shifters for the vehicle holding decision. Variables used in estimating coefficients for MITRAM equations are defined in Table 8.

The conventions used in presenting equations are as follows.

- For a real-price series in constant dollars as of a particular year, the year and a dollar sign are added after the variable. Thus, for example, **TX(83$)** indicates real spending per person per year on taxis, expressed in 1983 dollars.

- For a price-index series in which a given year is set to a base value of 100 or 1.00, the base year is added in parentheses after the variable. When the price index is a nominal price index, an "n" is added before the year, and an "r" is added if the price index is a relative price index (generally, one deflated by an aggregate consumer price index). Thus, for example, **CPI(n78)** refers to the nominal BLS consumer price index with 1978 as the base year, whereas **CUCI(r78)** refers to the BLS used car index when deflated by the CPI, both with the base year 1978.

- Negative subscripts indicate years of lag in the given variable, i.e., "-1" indicates a 1-year lag.

- Coefficients are presented to the left of the variable to which they apply, and under the coefficient is its t-value. If a coefficient is statistically significant using the one-tail test and a 10% level of significance, a single asterisk is next to the t-value. Generally, a high t-value indicates that a variable explains a larger share of the variation than other variables.

- Several statistics may be presented for each equation. R^2 is a measure of the "goodness-of-fit" of an equation to the raw data; it can vary from 0 to 1.0. If the equation has been estimated by ordinary least squares (OLS) regression, the adjusted R^2 value for the equation is presented as $\bar{R}^2$. $\bar{R}^2$ is based on the number of observations and the number of variables in the equation; it is always lower than R^2. The F-values is a statistic used here to measure the statistical significance of an entire equation. The

TABLE 8 Variables Used in Estimating Coefficients for MITRAM Equations

Variable	Definition	Data Sources
CMNCI	New car index (based on the CPI index up to 1973 and sales-weighted list prices thereafter)	Refs. 14 (1987) 18, and 26
CPI	Bureau of Labor Statistics consumer price index for urban residents	Ref. 14 (1987)
CUCI	CPI used car index deflated by the aggregate CPI	Ref. 14 (1987)
G	Sales-weighted price of all gasoline relative to all consumer prices	Ref. 13
MV	Miles of travel per vehicle (called VMT in text)	Ref. 8
NMPG	New car fleet miles per gallon as rated by EPA	Refs. 12 and 16 (1987)
ORFFE	Total new and used private car fleet on-road (actual) fuel economy (miles per gallon)	Ref. 13
PBTR	Spending per household on public transportation, equals TRCR + TXS	
TR	Price index for local public transportation, in constant dollars	Ref. 6
TRCR	Real spending per capita per year on public transportation and commuter railroads	Ref. 6
TRVH	Transit vehicles owned or leased per U.S. household	Refs. 12 and 27
TXP	Price index for taxis in constant dollars	Ref. 6
TXS	Real spending per person per year on taxis	Ref. 6
UR%	Percentage of U.S. population in urban areas of more than 500,000 persons	Ref. 12[a]
VC	Private vehicles registered per capita (mid-year population)	Refs. 8 and 28
VH	Private registered vehicles per household	
WC	Workers per capita (civilian noninstitutional labor force)	Ref. 29
WH	Workers per household	
WV	Workers per private vehicle	
YC	ln(income per capita) - ln(lowest NPTS sample household income)[b]	
YH	ln(household income) - ln(lowest NPTS sample household income)[b]	
YH10	ln(household income) - ln($10,000), in 1983 dollars	Ref. 12

[a]1984 edition, Table 26, using interpolated values based on 1960, 1970 and 1980 censuses.

[b]$1,588 in a single-person household (1983 dollars).

Durbin-Watson statistic (D-W) and the number of observations (N) are also presented. The D-W value can range from 0.0 to 4.0, and it equals 2.0 if no autocorrelation exists. When Durbin-Watson statistics are poor, a corrected equation, developed using the "Forecast Master" software package (Scientific Systems, Inc., 1986), is presented. For the corrected equations, the R^2 value and the F-value are not presented, because by definition, the correction for autocorrelation will raise these values.

In principle, vehicles per household (**VH**) and spending per household on public transportation (**PBTR**) are substitutes for one another that are simultaneously determined. More spending on one means less on the other, leading to an expectation of a negative sign for the influence of each on the other. Household income (**YH**) is expected to raise the demand for trips. After accounting for the effects of car usage, this should be reflected as an increase in public transportation spending as income rises. Income is expected to more strongly positively influence private vehicle ownership and use than public transportation use. After accounting for the effects of income, the number of jobs held is expected to increase the demand for both public transportation and private vehicle ownership. When the number of workers per household (**WH**) or per person (**WC**) rises, it is expected that more cars will be required. When the jobs obtained do not provide enough income to allow use of private vehicles, then the number of workers per vehicle (**WV**) will rise and the demand for public transportation should increase. The relationship between number of workers and private vehicle demand is absent from the vehicle-holding models reviewed in Sec. 3, although some do include an employment measure such as unemployment. However, the worker variable here, which measures the effect of labor participation, is different. Its use is an important nuance that helps to account for the recent years' phenomenon of increasing demand for private vehicles in spite of decreasing real income per person employed.

Increases in gasoline price (**G**), by increasing the costs of private vehicle use, should have a negative effect on vehicle ownership. The effect on public transportation use is more ambiguous. By increasing the costs of private vehicle use, gasoline cost increases should cause a shift to public transportation, and the variable should have a positive sign reflecting real gasoline price effects on real transportation spending. On the other hand, rising fuel costs should have some effect on the operating cost of public transportation, possibly causing an increase in public transportation fares and thereby a reduction in use of public transportation. However, if the cost of public transportation (**TR**) is accounted for, the effect of gasoline prices on public transportation use should be unambiguous. There should be a negative effect (own-price effect) of higher real transit price on real transit spending (**TRCR**), but positive effects (cross-price effects) of higher costs of using private vehicles on the decision to switch to transit. Thus both real car costs (**CUCI** or **CMNCI**) and real gasoline prices should have a positive effect on real spending on public transportation.

The effects for spending on taxis (**TXS**) are less because the costs of taxi services (**TXP**) should move in the same direction as the costs of private vehicles. Although the effect of higher costs of private vehicles on taxi use (after accounting for the costs of taxis) should be positive on the consumer-demand side, the effects could be negative on the taxi service supply side because higher real private vehicle costs should force taxis out of business.

A higher cost of private vehicles should reduce their use, so there should be a negative relationship between vehicle cost (**CUCI** or **CMNCI**) and vehicle use (**VC, VH,** or **MV**), as well as a negative relationship between real gasoline cost and vehicle use. The higher the fuel economy (**NMPG** or **ORFFE**), however, the lower the cost of operating a vehicle. Thus, higher fleet fuel economy should increase use of private vehicles.

Finally, with regard to public transportation, two additional effects not presently included in MITRAM were tested. These are both "level-of-service" indicators for local public transportation. One is the number of transit vehicles in service per U.S. household (**TRVH**), and the other is the share of the population living in urban areas of greater than 500,000 population (**UR%**). As Sabouni has shown, such cities are where transit can be most effectively provided.[30] The share of U.S. population in such cities declined over the last three decades. Increases in either of these variables should increase transit use. Both, however, have declined appreciably over the last three decades, as has the rate of real spending on transit.

In terms of expected signs for independent variables of equations, the prior discussion can be summarized as follows:

MV, VH, or VC = f[(+)YH, (+)WC, (-)G, (-)CUCI, (-)CMNCI, (+)NMPG,
(+)ORFFE, (-)PBTR]

TRCR = f[(+)YH, (+)WC, (+)WV, (-)TR, (+)G, (+)CUCI, (+)CMNCI,
(-)NMPG, (-)ORFFE, (-)VH]

TXS = f[(+)YH, (+)WC, (+)WV, (-)TXP, (?)G, (?)CUCI, (?)CMNCI,
(?)NMPG, (?)ORFFE, (-)VH]

The regression equations that resulted from testing for these and other relationships are described in the following sections.

4.1 PRIVATE VEHICLES REGISTERED PER HOUSEHOLD, 1960-1985

The initial equation is:

$$\underset{(-1.71^*)}{VH = -0.65} + \underset{(8.02^*)}{0.51\ YH} + \underset{(3.36^*)}{0.61\ WH} - \underset{(-3.65^*)}{0.16\ CMNCI_{-1}} - \underset{(-6.59^*)}{2.07\ TRCR} \qquad (1)$$

$\bar{R}^2=0.99$ $\quad F(5,21)=447.7^*$ $\quad D\text{-}W=0.62^*$ $\quad N=26$

In view of the severe positive autocorrelation represented by the Durbin-Watson value well below the desired value of two, a corrected equation was estimated:

$$VH = \underset{(-0.33)}{-0.14} + \underset{(4.67^*)}{0.41\ YH} + \underset{(1.32)}{0.39\ WH} - \underset{(-2.37^*)}{0.13\ CMNCI_{-1}} \qquad (2)$$

$$- \underset{(-0.39)}{0.29\ TRCR} + \underset{(20.56^*)}{0.93\ A_{-1}}$$

The A_{-1} term is the autocorrelation correction. (After correcting any equation, we checked the correlogram for further significant autocorrelation, ran diagnostic tests for trend, addition of a lagged dependent variable, nonlinearity, and heteroscedasticity, and ran an autoregressive conditional heteroscedasticity (ARCH) process to insure no further problems with the equation.) Two changes in the corrected coefficients require further evaluation. The decline in the coefficient of the employment variable (**WH**) suggests that this variable may not be important. The substantial decline in the coefficient of local public transportation spending variable (**TRCR**) suggests that public transportation does not have the ability to substitute for private vehicles; however, the sign of the coefficient is negative, as expected, even after correction. The validity of the OLS estimates of the coefficients will be compared with those of the corrected equation by recalibrating versions of these equations with household attribute information from the 1977 and 1983 NPTS samples. Since the national aggregates cannot capture the important effects for low-income minorities, the regression is likely to reflect majority characteristics.

4.2 REAL SPENDING PER CAPITA PER YEAR ON LOCAL PUBLIC TRANSPORTATION AND COMMUTER RAILROADS, 1960-83

We discussed in Sec. 2 household responses to the oil price shock of 1978-80. The trade-off of private vehicles vs. public transportation was an especially important part of the response of low-income households in general and low-income Hispanic and black households in particular. However, explaining household behavior for the 1977-83 interval does not provide data that can be used in modeling, and while logic and theory can be used to deduce the probable explanation for the behavior, it may not be possible to statistically support the explanation.

The question is whether the level and cost of public transportation services can be shown to influence car ownership and use decisions, after taking in account the effects of income and car ownership. There is little doubt that the converse is true, namely, that car ownership and use influences decisions about public transportation use. It is generally recognized that, for the average household, private transportation is superior to public transportation, so that once a vehicle is purchased, it is used as the primary means of travel. The availability and cost of public transportation predominantly influence the vehicle ownership decision rather than the vehicle use decision.

In principle, the question of whether car influences transit or transit influences car is best addressed by methods such as two- or three-stage least squares regression. Although such methods have not been used in this study, some progress toward constructing such equations has been made. Because of the potential importance of the question for public policy, a public transportation equation not used in MITRAM will also be presented. Few of the models of the vehicle-holding decision (Table 4) include an estimate of the influence of public transportation. (However, when such an estimate was made, it consistently indicated that public transportation use reduces vehicle ownership or use.) None of the prior models included a separate equation estimating the use of public transportation.

Equation 3 is not used in MITRAM, but it does show that studied but unmodeled effects are important, using statistical significance as the criterion for importance. The constant term for this equation was negative (at $21/year) and insignificant; the term was dropped with little effect on coefficient estimates and no effect on which of the coefficients were statistically significant.

$$\begin{aligned} TRCR(r83\$) = {} & \underset{(2.90^*)}{80.62\ YH} + \underset{(9.52^*)}{98.97\ TRVH} - \underset{(-3.28^*)}{84.68\ VH} - \underset{(-12.29^*)}{74.28\ TR(r83)} \\ & + \underset{(1.05)}{0.064\ G(r83\$)} + \underset{(3.47^*)}{0.26\ CUCI(r83)} + \underset{(3.76^*)}{2.43\ UR\%} \end{aligned} \tag{3}$$

R^2=0.996 $\bar{R}^2$=0.994 F(7,16)=628.2* D-W=1.78 N=23

The data series (from 1960 to 1983) ends because of a 1984 revision in the method of collecting data on owned and leased transit vehicles.[27] Because autocorrelation is not indicated by the D-W value, this OLS estimate is acceptable. The signs of the coefficients are as expected and, with the exception of that for gasoline prices, each coefficient is statistically significant. The results strongly support the contention that spending on public transportation is price-sensitive over the long term (the **TR** coefficient) and that a high level of service, i.e., more transit vehicles per household (the **TRVH** coefficient), will increase real spending on public transportation. Also, based on the coefficient for **UR%**, if a failure occurs in public transportation, it is evidently tied in part to the broader relative failure of large U.S. urban areas.

Inputs to MITRAM from related models being developed for the Office of Minority Economic Impact do not include variables such as **TRVH, TR,** or **UR%.** Because the development of the public transportation components of MITRAM came late in the project, it has not been possible to use these variables. Consequently, a simpler equation using a more limited set of variables is now used in MITRAM. The OLS version of that equation is:

$$\begin{aligned} TRCR(r83\$) = {} & \underset{(-7.39^*)}{-44.08} + \underset{(31.16^*)}{44.51\ (1/VC_{-1})} + \underset{(2.40^*)}{0.08\ G(r83\$)_{-1}} \\ & - \underset{(-4.46^*)}{0.68\ NMPG_{-1}} \end{aligned} \tag{4}$$

$\bar{R}^2$=0.985 F(4,22)=355.64* D-W=0.96* N=26

The data series runs from 1959 to 1985. In view of the significant autocorrelation, a corrected equation was estimated:

$$TRCR(r83\$) = \underset{(-2.69^*)}{-36.48} + \underset{(10.69^*)}{42.35}\ (1/VC_{-1}) + \underset{(1.35)}{0.063}\ G(r83\$)_{-1} \tag{5}$$

$$- \underset{(-2.97^*)}{0.73}\ NMPG_{-1} + \underset{(2.71^*)}{0.58}\ A_{-1}$$

The equation indicates that when the number of private vehicles per capita (**VC**) is low, public transportation is substituted for cars. When real gasoline prices (**G**) rise, households switch from cars to public transportation. Conversely, when fuel efficiency of vehicles increases (**NMPG**), households switch toward the use of private vehicles. The lagged values of persons per car used in this equation were slightly superior to contemporaneous values tested in another equation; a second reason for using the lagged variable was to avoid simultaneity problems in the MITRAM calculations. The gasoline variable was clearly statistically best with a lag, and new car fuel efficiency should take a year or two to have a significant effect on transit choices.

4.3 REAL SPENDING PER PERSON PER YEAR ON TAXIS, 1960-85

The data series for taxis extends from 1960 to 1985. The OLS equation is:

$$TX(r83\$) = \underset{(4.61^*)}{80.23}\ WV + \underset{(9.66^*)}{119.96}\ WC - \underset{(-4.13^*)}{0.24}\ G(r83\$) - \underset{(-3.97^*)}{0.912}\ NMPG_{-1} \tag{6}$$

$$- \underset{(-4.36^*)}{55.04}\ CMNCI(r83)_{-1}$$

$R^2=0.885$ $\bar{R}^2=0.856$ $F(5,21)=30.91^*$ D-W=1.65 N=26

The constant term, which was negative and insignificant, was dropped from the equation. This did not affect the statistical significance of any of the reported coefficients; the largest change was a 22% decline in the workers per capita (**WC**) coefficient.

Reasonable interpretations of each of the coefficients are possible, but those for vehicle use costs are somewhat contradictory. The positive coefficients of workers per capita and workers per vehicle (**WV**) were expected, but the signs of the remaining coefficients were uncertain. In versions of the equation that included a real taxi price index, the estimated price of taxi service had an insignificant effect on spending. The cost of providing taxi service, influenced by gasoline prices (**G**) and new car costs (**CMNCI**), could have a negative effect on the success of taxi service business, thereby reducing real spending on taxis through a restriction in supply; the coefficients support this interpretation. However, if this effect were dominant, the coefficient of the new car fuel economy (**NMPG**) variable should be positive. Improvements in fuel economy of new cars could also cause households to shift back toward private vehicle use. The fact that the coefficients of $\mathbf{NMPG}_{-1}$ in Eqs. 5 and 6 are both negative and about the same (0.7 and 0.9) for the two types of public transportation spending examined suggests that the dominant effect is the switching from public transportation to private vehicles when the latter improve in fuel efficiency.

Like **NMPG**, the variable **WV** exhibited about the same effect on spending for local public transportation and for taxis, with both coefficient estimates in the neighborhood of $100/year per added worker per vehicle. However, $100 buys considerably fewer taxi trips than local public transportation trips; this shows up clearly in the NPTS data. Although total national spending on taxis is almost the same as for local public transportation and commuter railroads combined, the number of trips per household by bus and rail was more than 10 times the number by taxi.

The expense of taxi trips would make them less attractive than public transportation in the event of a gasoline price increase, and this is reflected in the results: **G** has a small negative coefficient for taxis and a small positive coefficient in the public transportation equation. The averages understate the importance of public transportation for the poor. Our NPTS sample indicated that low-income households not only increased the proportion of trips taken by bus and rail during the period 1977-1983, they also increased the absolute number of trips. This occurred in spite of a decline in total trips per household. Closer examination showed that this low-income effect was entirely due to choices of minority households. Low-income white households reduced their use of buses and commuter rail, in spite of the cost advantages. Other income groups reduced the proportion of trips on public transportation (as well as the total) during the same period.

4.4 PRIVATE VEHICLES REPORTED PER CAPITA IN SAMPLED U.S. HOUSEHOLDS, 1977 AND 1983

Because NPTS data reveals that many minority households behaved very differently than white households from 1977 to 1983, the regression results obtained with a relatively few observations of national aggregates cannot be trusted to describe minority behavior. Nevertheless, without good time-series data to prove otherwise, minority households must be assumed to respond to changing economic conditions exactly the same as the majority. On the average, this is not a bad assumption. However, when data allow it to be checked, a modification of the regressions to take into account minority household behavior is desirable.

The autocorrelation adjustment for the vehicle-holding equation, Eq. 2, resulted in a sharp decrease in the coefficient for the variable of public transportation spending (**TRCR**). Given this reestimate alone, one should conclude that there is no effect. However, minorities appear to have adjusted between 1977 and 1983 as the theory would suggest, while the majority apparently did not. Because the national aggregates are dominated by majority behavior, it is desirable to reexamine the relationship between transit spending and vehicle holding, treating minority behavior separately.

An aggregate regression estimate of vehicles held per person developed from the NPTS cross-sectional sample provides support for the argument that the availability of public transportation does reduce vehicle holding by households and individuals. Additional variables are defined in Table 9.

$$\begin{aligned} VC = & \underset{(-5.75^*)}{-0.18} + \underset{(38.57^*)}{0.36\ YC} + \underset{(2.44^*)}{0.005\ EH} + \underset{(3.02^*)}{0.018\ HEH} - \underset{(-2.16^*)}{0.056\ A1} \\ & - \underset{(-2.98^*)}{0.091\ TA1} + \underset{(3.48^*)}{0.096\ A2} - \underset{(-2.68^*)}{0.090\ TA2} + \underset{(6.62^*)}{0.16\ A3} - \underset{(-23.92^*)}{0.31\ PTA} \\ & + \underset{(33.56^*)}{0.14\ SHPW} - \underset{(-17.37^*)}{0.10\ BSHPW} - \underset{(-10.47^*)}{0.10\ HSHPW} - \underset{(-6.21^*)}{0.08\ OSHPW} + \underset{(54.65^*)}{0.63\ WC} \\ & - \underset{(-9.86^*)}{0.16\ BWC} - \underset{(-4.22^*)}{0.15\ HWC} + \underset{(4.25^*)}{0.06\ TWC} \end{aligned} \tag{7}$$

R^2=0.409 F(17,20617)=839.45* N=20,634

This equation, which includes 17 variables and is estimated on the basis of 20,634 observations, provides more detail about the effects of household characteristics than can the time-series equations with only about 25 observations. The large number of observations gives far more information about the causes and degree of variability of household behavior (thus the low R^2 value), allowing the testing of many more hypotheses. The only coefficients in Eq. 7 used to select coefficients for the considerably simpler MITRAM equations were those for **YH, WC, BWC, HWC,** and **PTA.**

In Eq. 1 the calculations are on a per household basis, whereas in Eq. 7 they are on a per capita basis. Since both right- and left-side values of the vehicle, worker, and income variables are divided by the same value in each of the two equations, the coefficients should be comparable. The **YC** coefficient (0.36) is similar to those of the **YH** variable obtained in the time-series Eqs. 1 and 2 (0.51 with OLS and 0.41 when corrected). The **WC** coefficient (0.63) in this equation is similar to the OLS coefficient (0.61) in Eq. 1, but is considerably higher than the corrected coefficient (0.39) in Eq. 2.* Overall, the similarity of these estimates gives confidence that they are robust. The coefficients of these two variables have the highest t-values in the NPTS cross-sectional equation, Eq. 7, supporting the selection of these variables for use in the time-series equations.‡

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*The use of the **SHPW** variable in this equation may elevate the **WC** coefficient. This possibility has not been checked. One test for similarity of cross-sectional and time-series estimates would be to rerun the regression for Eq. 7 using only those variables in Eq. 1.

‡The process of developing the cross-sectional and time-series versions of the vehicle-holding equations involved a number of experiments using equations with different variable structure and different sets of variables. The objective was to get a pair of equations for which the income and employment (worker) coefficients were comparable. Difficulty in reconciling time-series and cross-sectional estimates is typical in econometrics. The important point is that both income and employment are certainly causes of vehicle ownership.

TABLE 9 Additional Variables for the Vehicles-per-Capita Equation

Variable	Definition
A1	Dummy variable that equals one if household head is less than 35 years old, zero otherwise
A2	Dummy variable that equals one if the household head is 34-50 years old, zero otherwise
A3	Dummy variable that equals one if household head is 49-65 years old, zero otherwise
BSHPW	Dummy variable that equals SHPW if household head is black, zero otherwise
BWC	Dummy variable that equals WC if household head is black, zero otherwise
EH	Education of household head (years of school)
HEH	Education of household head in Hispanic households (years of school)
HSHPW	Dummy variable that equals SHPW if household head is Hispanic, zero otherwise
HWC	Dummy variable that equals WC if household head is Hispanic, zero otherwise
OSHPW	Dummy variable that equals SHPW if household head is a minority other than black or Hispanic, zero otherwise
PTA	Dummy variable that equals one if public transit is within 24 blocks (2 miles) of household, zero otherwise
SHPW	Number of household members per employed person in household (in zero worker households, the number of workers was set to 0.5)
TA1	Dummy variable that equals one if A1 = 1 and sample year is 1983, zero otherwise
TA2	Dummy variable that equals one if A2 = 1 and sample year is 1983, zero otherwise
TWC	Dummy variable that equals WC if household is from the 1983 sample, zero otherwise

Although the differences between minorities and the majority are important, it is desirable to keep the magnitude of the differences in perspective. In earlier tests with a nearly identical equation, removing all race, age, and time-related variables only lowered R^2 from 0.406 to 0.384. Thus, it is important to remember that responses to factors such as income, education, employment, and household size are far more important than race in determining typical household behavior.

The cross-sectional analog to the **TRCR** variable used in the time-series models is the public transit access (**PTA**) variable. The coefficient of **PTA** in Eq. 7 is easily significant, and the t-value of the coefficient is the fourth largest among the variables included in the equation. This strong result, based on a large number of observations of households of all types, tends to support the OLS time-series estimate of a large, significant coefficient for **TRCR**.

Although there is no vehicle price variable in the NPTS sample, the negative coefficients of **TA1** and **TA2** are consistent with the 1977-83 rise in real vehicle prices causing a decline in vehicle holding from 1977 to 1983. According to the values for **CMNCI** and the time-series coefficient in Eq. 1, the effect of increases in new car price would have caused only a 0.01 vehicle per person decline during this period. The coefficients of **TA1** and **TA2** imply a sharper decline for a large segment of households, i.e., those with heads younger than 50. However, this effect is offset by the 0.06 coefficient for the dummy variable for workers per person (**TWC**) in 1983. The age results imply that younger households, with less wealth and a propensity to drive more, were affected more by rising vehicle and gasoline prices than were older households. The coefficients of **A1, A2,** and **A3** suggest that households with a head under 35 owned fewer vehicles per person than households with a head over 64. Further, the coefficients suggest that vehicle ownership per person rises with age through retirement and then declines. This pattern is consistent with an increase in vehicle consumption as a function of wealth during the time that wealth is increasing.

The results for the household size variables (**SHPW, BSHPW, HSHPW,** and **OSHPW**) imply that more household members per employed person demand more mobility, raising the number of vehicles held. Although the net household size coefficient (obtained by subtracting the **SHPW** minority dummy variable coefficients from the white coefficient) is positive for minorities (black = 0.04, Hispanic = 0.04, other = 0.06), it is significantly less strong for minorities than for whites (= 0.14). The positive coefficients of **EH** and **HEH** suggest that education also increases the demand for mobility, thereby increasing demand for vehicles. The coefficient for the Hispanic education variable (**HEH**) is noteworthy because it is the only case in the equation in which a minority effect is estimated to be positive. The black and Hispanic variables for the effect of employment (**BWC** and **HWC**) imply that acquisition of an additional job by a black or Hispanic household is less likely to result in an additional vehicle for the household than for whites and other minorities.

4.5 PRIVATE VEHICLES REPORTED PER HOUSEHOLD MEMBER VS. PUBLIC TRANSPORTATION SPENDING, 1977 AND 1983

Development of the final coefficients for use in MITRAM involved adaptation of the time-series equations to the cross-sectional information in the NPTS sample. This process involved several steps, including the use of the NPTS information to improve the coefficient estimates for Eqs. 1 and 2. First, note that although there are no values of the time-series variables of car prices (**CMNCI**) or public transportation spending (**TRCR**) within our NPTS sample, there is some basis for attaching estimates of those values to statistical descriptors developed from the NPTS sample. In the case of car prices, the national values for the years 1983 and 1977 can be attached to household observations made in these years. In the case of public transportation spending, more detailed estimates of spending by households can be constructed, given the availability of information on trips made by bus, commuter railroad, and taxis. A good **CMNCI** coefficient is easy to select, given that the OLS value in Eq. 1 is 0.16, the corrected value in Eq. 2 is 0.13, and both are significant. However, given the extreme differences between the **TRCR** coefficients in Eq. 1 (-2.07) and Eq. 2 (-0.29), and the statistically significant value of the public transit access (PTA) variable in Eq. 7, selection of a proper coefficient for this variable is difficult. The crude procedure we have used to select the coefficient used in MITRAM is discussed in this section. A major consideration is whether the inverse interaction between public transportation use and private vehicle use is important for minorities in general and low-income minorities in particular.

Creating household-specific estimates of public transportation spending for characteristic household groups in the NPTS sample is a two-step process. First, the national spending estimates from the PCE data[6] were allocated nationally to households based on the NPTS estimates of trips per household by race and the national estimates of households by race. It was assumed that spending per trip was constant. This resulted in a year-specific estimate of average national spending per trip for "local public transportation" (treated as equivalent to NPTS bus and commuter rail trips). With these estimates and the average number of trips of each type by race and income, it was possible to construct estimates of total spending on local public transportation and estimates of the share of income devoted to public transportation by income and race (Table 10).

The estimated share of spending devoted to public transportation drops sharply with rising income. For a national average household, the share devoted to public transportation is quite small (about one quarter of one percent of household income). For low-income black households, however, the share is about eight times the national average and for low-income Hispanic households, five to six times. Clearly, these values imply that policies contributing to a real rise in fares for public transportation are regressive in general and particularly regressive with respect to low-income Hispanic and black households. The estimated "within-race" regressivity is greatest for Hispanics. High-income Hispanic households appear to spend money on public transportation in much the same manner as whites, but low-income Hispanics spend more like blacks than like whites.

4.5.1 Low-Income Household Spending

The relative importance of public transportation spending for low-income blacks is best understood by comparing it to spending on vehicles and gasoline. The NPTS sample indicates that low-income black households averaged about 2,400 VMT per year. Assuming vehicles that average 12 mpg (a value based on 1983 RTECS data[31] for on-road mpg of specific model-year vehicles, according to race) and gasoline at a 1977 and 1983 average of $1.10 in 1983 dollars, this group would have spent $220 per household on gasoline vs. about $100 on public transportation. These out-of-pocket transportation costs represent about 6.5% of the NPTS mean class household income for low-income minorities. The NPTS household data indicate that low-income Hispanic households and low-income white households drive more (approximately 4,500 and 5,000 miles/year, respectively), and the RTECS vehicle-specific data indicate that whites and Hispanics owning 1971-76 model cars enjoyed about 2 mpg more than blacks owning cars of the same model years.[31] Using approximately these numbers, Hispanics would have averaged

TABLE 10 Estimates of Total Spending and Share of Income for Public Transit

Household and Income (1983 $, thousands)	Total Amount Spent ($)		Income Share (%)	
	1977	1983	1977	1983
White				
<10	23	17	0.43	0.32
10-24.9	48	27	0.28	0.15
>25	46	26	0.11	0.06
All	44	26	0.17	0.10
Black				
<10	101	96	2.05	1.94
10-24.9	167	165	1.06	0.98
>25	144	211	0.38	0.56
All	138	143	0.84	0.94
Hispanic				
<10	69	88	1.20	1.52
10-24.9	143	142	0.90	0.89
>25	72	26	0.19	0.09
All	105	105	0.57	0.54
All	65	53	0.26	0.21

about $435/year in out-of-pocket expenses in 1977 and 1983, amounting to about 7.6% of the NPTS mean class household income. Whites would have averaged about $430/year, amounting to about 8% of the somewhat lower mean income for sampled white households in the low income class. These figures imply that low-income blacks spend a smaller share of income on out-of-pocket transportation costs, but these figures do not include spending on taxis.

Using national values for number of households and our NPTS estimates of taxi trips per day by race, we estimated the total number of household taxi trips in 1977 and 1983. These national values were divided into the PCE national estimates to obtain an estimate of the 1983-dollar cost per household taxi trip, which was about $10 per trip in both 1977 and 1983. Although this seems high, it is consistent with the average distances reported for taxi trips, which ranged from 13.6 miles for nonwork trips in both 1977 (n = 81) and 1983 (n = 24) to 14.7 miles for work trips in 1977 (n = 16) and 19.0 miles (n = 5) for work trips in 1983. The NPTS estimates indicated that the predominant use of taxis was for nonwork trips, while trips on buses and commuter rail were about evenly divided between work and nonwork. Using the $10/trip value, annual expenditures on taxis can be estimated. For low-income black households, which use taxis far more than do whites or Hispanics, the average annual expenditure for 1977 and 1983 was estimated to be $125. For whites, the estimate was only $30, and for Hispanics it was $5. If these values are added to the above totals, the estimated share of out-of-pocket transportation expenditures rises to 9.0% for low-income black households and to about 8.5% for whites.

If taxi costs per trip were only $4, the expenditure share would become 7.5% for low-income blacks, 8.2% for whites, and 7.6% for Hispanics, and the percentage of out-of-pocket transportation expenses for taxis, buses, and commuter railroads would be 40% for low-income black households, 18% for Hispanics, and 7% for whites. As one would expect, the groups using transit the most depend on private vehicles the least. The NPTS-based estimate of the 1977 and 1983 average of vehicles held per low-income household was 0.46 for blacks, 0.62 for Hispanics, and 0.82 for whites. At $4 per taxi trip, the pattern of vehicle holding and public transportation use by blacks, Hispanics, and whites (with income roughly constant) shows public transportation substituted for vehicle ownership, consistent with the OLS-based, statistically significant relationship between local public transportation spending and vehicle holding per capita. In this case, support for the OLS version of the **VC** time-series model (Eq. 1) is provided.

A value of $4 per taxi trip is used in the tables presented below and for the cost computations in MITRAM. The basis for this decision was discomfort with the $10 value estimated using national statistics; this is an area worthy of further study. With only 97 observations in 1977 and 29 in 1983, the taxi trip data are suspect; short, inexpensive taxi trips may have been underreported. The taxi expenditure issue is an important one to resolve. Surveys of taxi companies might help narrow the uncertainty.

Another important pattern of behavior influencing fuel consumption and expenditure estimates in 1977 and 1983 is the purchase of newer cars by higher-income groups. Our analysis of RTECS data showed that the higher the income level, the lower the average age of the car. In the 1977-83 timeframe, this meant that more fuel-efficient cars were held, on average, by higher-income households. Shares of income devoted to out-of-pocket transportation costs (Table 11) were calculated based on the crude assumption that nonblack households with incomes above $10,000 owned cars that attained the U.S. average on-road fleet fuel economy (12.5 mpg in 1977 and 17.7 mpg in 1983) and that blacks had about 10% lower economy (discussed later).

The 1977 and 1983 estimates in Table 11 have some interesting implications. First, within a given income class, the estimates of both trips per household and the percentage of income devoted to out-of-pocket transportation costs were roughly constant for whites, Hispanics, and blacks. Second, the composition of transportation expenditures for a given income varies substantially and consistently by race. For all three income classes, whites devote the smallest share of out-of-pocket transportation expenditures to taxi, bus, and commuter rail trips, and blacks devote the largest share to such trips. The substitution of public transportation for private vehicles clearly shows up in the household vehicle ownership patterns. For all three income classes, whites own the largest number of vehicles per household, and blacks own the least. From these comparisons, it is clear that the higher the amount of spending by minority groups on public transportation for a given income, the lower the number of vehicles owned by the minority group. This clearly contradicts the earlier finding (Eq. 2) that this substitution effect was insignificant.

TABLE 11 **Transportation Spending as Share of Income (NPTS-based estimates, averages for 1977 and 1983)**

Household and Income ($ thousands)	Percent of Income Devoted to: Fuel	Taxi[a]	Fuel and Taxi	Transit	All Three	Share[b] for Taxi and Transit (%)	Per Household: Vehicles	Trips
White								
<10	7.6	0.22	7.8	0.4	8.2	7.2	0.8	2.9
10-24.9	6.0	0.06	6.1	0.2	6.3	4.4	1.7	5.1
>25	3.8	0.04	3.8	0.1	3.9	3.1	2.3	6.8
Hispanic								
<10	6.2	0.03	6.2	1.4	7.6	18.2	0.6	3.1
10-24.9	4.8	0.07	4.8	0.9	5.7	16.7	1.4	5.1
>25	3.7	0.04	3.8	0.1	3.9	4.6	2.1	5.9
Black								
<10	4.5	1.01	5.5	2.0	7.5	39.9	0.5	3.0
10-24.9	4.4	0.22	4.7	1.0	5.7	21.9	1.2	5.1
>25	3.5	0.08	3.5	0.5	4.0	13.6	1.8	6.2

[a]Assuming $4 per trip.

[b]Share of out-of-pocket transportation spending.

Another implication of the data in Table 11 is that high-income households are most similar in their shares of income spent on gasoline. However, as income drops, the differences in this spending by race increase dramatically, with the spending on fuel less for Hispanics than whites and still less for blacks than Hispanics. Despite these differences, the data indicate that the share of income spent on gasoline rises as income declines for all races. Thus, a gasoline tax would be regressive, hurting poor households the most, contrary to assumptions made by at least one advocate of the gasoline tax.[32] However, poor black households should suffer least from the regressive nature of the tax and poor white households would suffer most. Further, the expenditure shares for taxis and transit (buses and commuter rail) imply that taxes or subsidy reductions affecting these means of transportation would be far more regressive than gasoline taxes.

The relative reduction in number of trips per income class as income declines suggests that trips are a necessity. Although the demand for trips decreases as income decreases, the rate of decrease in demand is far slower than the rate of decline of income. Demand for trips is therefore income-inelastic, which causes the estimated share of income devoted to out-of-pocket trip costs of the lowest income class to be roughly twice that of the highest income class, regardless of minority or majority status.

These estimates are reasonable compared with the estimates generated in MITRAM.[1] The version of MITRAM developed from this research creates expenditure share estimates only for mean household incomes for whites and blacks over the 1985-95 interval. The mean income value is over $25,000 (in 1983 dollars) for whites and over

$16,000 for blacks. Gasoline was more expensive in 1977 and 1983 (Table 11) than in the 1985-95 base period used in MITRAM, and the vehicle fleets in 1977 and 1983 of black and white households were less fuel-efficient. Thus, the shares of income spent on gasoline and all transportation are estimated to be less in MITRAM than those for comparable income levels in Table 11.

Although out of pocket transportation expenditure shares (the "All Three" column of Table 11) are estimated to be comparable by income for blacks, Hispanics, and whites, the proportion of households in the three income categories differ greatly. Blacks are far more likely than whites to have low incomes, so their aggregate share of income devoted to out-of-pocket transportation costs should be larger (on average). The MITRAM estimates agree. Because blacks become more dependent on public transportation and taxis as their income declines, the base case MITRAM estimates of aggregate gasoline spending by black households are slightly below those for whites.

Dollar costs are only one indicator of consumer welfare. If one were to define consumer welfare in terms of the average cost of traveling a given distance, including the value of time spent, the dependence on public transit of blacks would probably increase their costs to levels well above those implied by using share of income spent. To illustrate, the average trip times for whites, blacks, and Hispanics as estimated from the 1977 and 1983 NPTS trip files were about the same. However, the trips taken by blacks and Hispanics were shorter and slower than those for whites, even after controlling for income (Table 12). This effect was especially pronounced for blacks. This means that although blacks spend about the same share of out-of-pocket income for transportation as whites and Hispanics, they get far less in terms of actual level of service. Unfortunately, we have not incorporated a measure of level of service (in economist's terms, transportation utility) into MITRAM at this time.

4.5.2 Reestimating Coefficients to Account for Race

The clear tendency to substitute public transportation for private vehicles revealed by this detailed consideration of NPTS-based estimates suggests that the theoretically best **VC** regression model (Eq. 2) might not actually be the best, because it indicates that the substitution of public transportation for vehicles is insignificant. Also, the substantial differences in vehicle ownership by race, which increase on a percentage basis as income decreases, suggest that the coefficients of the income and employment variables might vary by race. The negative coefficients of the race-specific worker dummy variables (**BWC** and **HWC**) in the cross-sectional results (Eq. 7) already indicated that this was the case for employment.

To test these possibilities, a set of pseudoregressions was constructed using the NPTS average characteristics for 12 classes of household, based on the three income classes used in Tables 10, 11, and 12, and on four household employment categories, i.e., (1) no employed persons in the household, (2) one, (3) two, or (4) three or more. The NPTS household averages of vehicles held per person were compiled for each of the 12 household classes for whites, blacks, and Hispanics, and for each of those, separately for 1977 and 1983. Sample mean values of the four independent variables in Eqs. 1 and 2 for each household type, each racial group, and each year were also constructed. Three sets

TABLE 12 Average Trip Characteristics by Income and Race (1977 and 1983)

Household and Income ($, thousands)	Time (min.)		Speed (mph)		Distance (miles)	
	1977	1983	1977	1983	1977	1983
White						
<10	17.7	12.6	30.5	25.4	8.9	9.1
10-24.9	30.2	21.4	27.9	27.3	15.8	10.4
>25	34.2	25.8	29.1	28.6	18.6	13.7
All	29.9	21.6	28.8	27.7	15.9	11.5
Hispanic						
<10	18.4	13.8	26.8	22.6	7.3	3.9
10-24.9	31.4	22.6	25.7	26.0	14.1	7.9
>25	32.6	22.8	27.8	28.8	15.9	11.0
All	27.9	19.8	26.6	26.4	10.2	6.5
Black						
<10	21.2	14.2	20.9	20.8	6.4	3.1
10-24.9	32.3	23.8	24.7	23.0	12.2	8.1
>25	28.6	18.4	25.8	25.5	13.6	12.1
All	27.8	20.2	23.8	23.3	12.5	7.5

Source: Refs. 4 and 5.

of separate trial coefficients of **CMNCI** and **TRCR** from Eqs. 1 and 2 and a modified Eq. 2 were then entered into three trial equations having the same structure, using the 1977 NPTS data.

$$VC = \beta_{1r} + \beta_{2r}YH_r + \beta_{3r}WC_r - 0.16\ CMNC_{-1} - 2.07\ TRCR + \mu_b \tag{8}$$

$$VC = \beta_{1r} + \beta_{2r}YH_r + \beta_{3r}WC_r - 0.13\ CMNC_{-1} - 0.29\ TRCR + \mu_b \tag{9}$$

$$VC = \beta_{1r} + \beta_{2r}YH_r + \beta_{3r}WC_r - 0.13\ CMNC_{-1} + \mu_b \tag{10}$$

where the values of β_{1r}, β_{2r}, and β_{3r} are determined for each racial group, r.

Holding the **CMNCI** and **TRCR** coefficients constant within each of these three equations, the constant term, the income (**YH**) coefficient, and the employment (**WC**) coefficient were varied for each of three racial groups (whites, blacks, and Hispanics) until a minimum sum of squared errors from the sample means ($\Sigma\mu_b^2$) was determined for each race, subject to the restriction that the sum of the errors for the 12 household categories equaled zero ($\Sigma\mu_b = 0$). The zero value for **TRCR** in Eq. 10 was entered to test whether the assumption of no transit effect was better than an effect of -0.29 or

-2.07. The specific values of β_{1r}, β_{2r}, and β_{3r} for whites, blacks, and Hispanics were determined from the 1977 NPTS data. The resulting values were then attached to the 1983 household class data in each of the three equations, along with 1983 values of **$CMNC_{-1}$** and **TRCR**. The **$CMNC_{-1}$** values varied only by year and not by household class or race. The estimated **TRCR** values varied by household income and by race, but not by workers in the household.

When examining the sums of squared deviations from the NPTS sample means for each equation separately within white, black, and Hispanic categories, the results were inconclusive. None of the three (Eqs. 8, 9, or 10) consistently resulted in the minimum sum of squares. Differences in sums of squares for the three white models were less than 2%. However, when the three versions of the model for whites were used to estimate minority behavior, Eq. 8 was always best, especially for blacks. Thus, if one were to desire a single model of dominant household behavior that could best reproduce minority behavior, models such as Eqs. 1 and 8, with large coefficients for the public transportation variable, would best reflect the effects of public transit use on vehicle holding. In the case of blacks, the sum of squared errors for the white version of Eq. 8 was far less than for the two competing versions in both 1977 and 1983.

Based on these and prior results, it was decided to use Eq. 8, with a coefficient of -2.07 for **TRCR,** as a standard equation in MITRAM. The version of the equation used in MITRAM, however, uses the specific β_2 and β_3 values determined for whites and blacks. The values of β_2 and β_3 determined for whites, blacks, and Hispanics are listed in Table 13, along with the values determined in Eqs. 1, 8, and 7. These coefficients are 0.36-0.75 for β_2 and 0.23-0.61 for β_3. There is no clear evidence that the time-series estimates are consistently higher or lower than the cross-sectional estimates. In principle, the coefficients in Eqs. 1, 2, and 7 should be better at predicting average behavior, whereas coefficients from the method described for Eq. 8 should be better in predicting the behavior of atypical households, because this method gave atypical households as much weight as typical households. For the black and Hispanic estimates, this means that the atypical high-income groups were given as much estimating weight as the far more common low-income households. By allowing the high-income category to carry so much weight, we theoretically avoid the pitfall that, because most blacks and hispanics are poor, they would behave similarly even if their income rose. Thus, to predict the vehicle holding patterns of black and Hispanic households if they attained the income levels of whites, the coefficients of Eq. 8 should be used.

The method used here to establish the transit coefficient (and related coefficients in the same equation) was an ad hoc method. There remains a great deal of uncertainty about the correct coefficient to use in estimating the effect of transit. A great deal of uncertainty also remains in many of the coefficients used in the model, and the public transit coefficient is the most uncertain. The certainty of a transit effect might be more clearly demonstrated from a more thorough review of the literature.

Within MITRAM, the constant terms in equations are generally adjusted as necessary to calibrate starting values to historical base values. The constant terms from the NPTS analysis are based on vehicle holding behavior of households with working-age heads. MITRAM, however, is calibrated to national data on vehicles registered per

TABLE 13 Summary of Coefficient Values Estimated for Income and Employment Effects on Vehicle Ownership per Capita

Equation No.	Equation Type	Population Group	Income Effect, β_2	Employment Effect, β_3
1	Time-series	All	0.51	0.61
2	Time-series	All	0.41	0.39
7	Cross-sectional	All	0.36	Note a
		White	0.36	0.63
		Black	0.36	0.47
		Hispanic	0.36	0.48
8	Cross-sectional	White	0.61	0.45
		Black	0.52	0.32
		Hispanic	0.75	0.23

[a]No estimate because of equation structure.

person. Because retirees are included in this group, the constant terms of the NPTS-based equations, which do not include retiree household heads, are higher than appropriate for the entire U.S. population. Thus, largely as a result of the differences in the sample population, the NPTS-based Eqs. 7 and 8 give higher estimates of vehicle holding per household than do the time-series-based Eqs. 1 and 2.

4.6 VEHICLE-MILES OF TRAVEL PER VEHICLE PER YEAR FOR AVERAGE U.S. HOUSEHOLDS

In estimating VMT, we have not relied on the NPTS sample for several reasons. First, to be useful in capturing price effects, the sample should include prices and observations over which price varies substantially. The NPTS samples did not include gasoline price. Further, for any given year, the geographic variation in gasoline prices has been far less than the variation with time over the last 20 years. Thus, for 1977 or 1983 alone, the NPTS sample would not do a good job of capturing the effects of gasoline price, even if the information were available. This is illustrated in the attempt by Train[2] to estimate the causes of variation in VMT per vehicle in one- and two-vehicle households. Operating cost was significant in the regression model for one-vehicle households but not in that for two-vehicle households. Income was significant for two-vehicle households but not for one-vehicle households. The R^2 value for both models was 0.11. An earlier VMT per vehicle model[7] based on the NPTS sample had a similarly low R^2 (0.14), even though it contained 20 statistically significant variables. An income variable in that equation had the highest t-value, and a worker-per-vehicle variable had the third-highest t-value.

The absence of cross-sectional gasoline price information might have been addressed by using the two separate sample years that were available. In principle, a national average gasoline price could be attached to the observations for each year in the pooled 1977 and 1983 samples and coefficients measuring the reaction of VMT per vehicle could be estimated. The NPTS data for VMT -- the household file and the trip file -- gave inconsistent results. Using the household file, VMT per vehicle would go up rather substantially, but using the trip file, VMT per vehicle would drop more rapidly than indicated by aggregate national data. The inconsistency exists because in 1983, households were asked how much other people had driven their vehicle in determining total vehicle VMT, but this was not part of the 1977 question. Our examination of the data suggested that the poor may have been particularly likely to assume that other people had driven their vehicle a considerable amount.

As a result of the inconsistency, we decided not to rely on a comparison of the 1977 and 1983 NPTSs in studying how VMT adjustments to gasoline price increases were made. In terms of other data sources, RECS-TP did not include the necessary information, and RTECS annual surveys did not start until 1983, making estimation of the reaction to the gasoline price shocks of the 1970s problematic.

MITRAM therefore contains two VMT-per-vehicle equations, both based on time-series estimates using national aggregate data, which are called the stock and the flow equations. Stock refers to the use of estimates of the grand totals of the dependent and independent variables to estimate the dependent variable. Flow refers to the use of estimates of changes of the dependent and independent variables to estimate changes in the dependent variable. Additional variables are defined in Table 14.

The stock equation is

$$\underset{}{MV} = \underset{(29.78^*)}{12.85} - \underset{(-5.91^*)}{0.305\ CM(r83)} - \underset{(-1.91^*)}{0.720\ GCH2_{-1}} - \underset{(-6.12^*)}{2.337\ CUCI(r83)} \quad (11)$$

$$+ \underset{(6.77^*)}{0.100\ YC(r83\$)\#}$$

$\bar{R}^2=0.90$ $F(5,19)=30.91^*$ $D\text{-}W=1.11^*$ $N=24$

The corrected version is

$$MV = \underset{(19.61^*)}{12.79} - \underset{(-5.54^*)}{0.343\ CM(r83¢)} - \underset{(-1.25)}{0.489\ GCH2_{-1}} - \underset{(-4.29^*)}{2.068\ CUCI(r83)}$$

$$+ \underset{(3.89^*)}{0.108\ YC(r83\$)\#} + \underset{(2.26^*)}{0.50\ A_{-1}}$$

The time period for this equation is 1960-84.

When the variable **WV** is added to this equation, it has a positive sign but is statistically insignificant. In a previous NPTS-based cross-sectional model, employment and income were both statistically significant, but the equation R^2 was only 0.14.[7]

TABLE 14 **Additional Variables for Vehicle-Mile Equations**

Variable	Definition
CM(r83¢)	Cost per mile in cents of driving an average registered vehicle in the fleet, equals ORFFE/G
ΔCM(r83¢)	Annual rate of change of operating cost of the average vehicle in the fleet, equals $\ln[CM(r83¢)/CM(r83¢)_{-1}]$
ΔCUCI(r83)	Annual rate of change of purchasing an average vehicle in the fleet (a used car), equals $\ln[CUCI(r83)/CUCI(r83)_{-1}]$
$GCH2_{-1}$	Percentage change in gasoline cost over two years, lagged one year, equals $(G_{-1}/G_{-3})-1.0$
ΔMV	Annual change in miles of travel per vehicle (VMT), equals $\ln(MV/MV_{-1})$
YC(r83$)#	Personal income per capita (thousands of 1983 dollars)[a]

[a]From personal income and population data, Ref. 28.

Similarly, a time-series equation using only employment, workers per vehicle, and income [**YC(r83$)#**] as exclusive predictors of **MV** had an R^2 of only 0.13. Further, the coefficients of the employment and workers per vehicle variables were insignificant in that equation (not reported here) and had signs opposite to those estimated in the cross-sectional model. In contrast, if only operating cost, **CM(r83¢)**, fuel cost change, **$GCH2_{-1}$**, and the used car price index, **CUCI(r83)**, are used to predict **MV** with this time series, the resulting R^2 is 0.66 (equation not reported here). These results tend to reinforce the point that the temporal variation of price (which is information not included in the NPTS) is a more important determinant of variations in VMT than is other information found in the NPTS. Interestingly, once the time-series effects of the price variables are accounted for, the incremental R^2 contribution of the income variable jumps from 0.10 in a simple regression to 0.24 when added into the multiple regression presented in Eq. 11.

The results of a similar time-series decomposition comparing price effects and public transportation effects to income and employment effects in the case of vehicle holding (Eqs. 1 and 2) were ambiguous. In that case, either equation did well and there was little basis for arguing that one group of variables is more important than the other. For Eq. 11, however, the importance of transportation prices clearly outweighs the household attributes of income and rate of employment. This is reflected in the flow equation (Eq. 12), in which tests of the latter two variables indicated no significant contribution after transportation cost effects have been taken into account. In the flow equation, only operating-cost changes and car-cost changes matter.

$$\begin{array}{llll} \Delta MV = & -0.001 & - 0.103\ \Delta CM(r83¢) & - 0.321\ \Delta CUCI(r83) \\ & (-0.24) & (-1.92^{*}) & (-8.25^{*}) \end{array} \qquad (12)$$

R^2=0.79 $\bar{R}^2$=0.76 F(3,21)=40.67* D-W=1.21 N=24

An important point about Eqs. 11 and 12 is that the variation in **MV** caused by the variables is very small relative to the average **MV** for vehicles in the fleet. In the case of the time-series values of average annual **MV**, the variation is only 3%. The mean **MV** for 1960-84 was 9,600 miles/year and the standard deviation about this mean was only 300 miles/year. This is because the decision to buy a car is also a decision to drive the car. Variations in fuel cost cause a very small change in annual cost of vehicle ownership, so once cars are purchased, the odds of them being driven about the same amount per year on average are great. These realities are reflected in the very low elasticity estimates in Eq. 12, as well as in the fact that the variables **CM(r83¢), G(r83),** and **CUCI(r83)** are themselves limited in the degree to which they vary over time.

Equations 11 and 12 are both used in MITRAM, and the results of each are averaged to obtain the "best" estimate of **MV**. Those users of MITRAM who suspect that one of these equations provides better results could modify the model accordingly.

4.7 CAUSES OF AND REACTIONS TO CHANGES IN NEW CAR FLEET MILES PER GALLON RATED BY EPA

Having the equations and coefficients used to estimate vehicle holding and vehicle use, all that is needed to estimate fuel expenditures is an estimate of fuel economy. As will become apparent, attainment of greater fuel economy in reaction to gasoline price changes not only influences vehicle operating cost directly, it indirectly influences the vehicle purchase decision for new and used cars (the fleet), as has been shown in prior equations. This latter reaction is actually more complex than is modeled in MITRAM, because MITRAM does not now model the new car purchase decision.

Alteration of fleet fuel economy in reaction to gasoline price changes is a several-step process. These steps are only approximated in the present version of MITRAM, but considerable work on the nature of the process was completed in the preliminary work on individual submodels. In this section, some of the work not included in the model will be presented for the record.

4.7.1 Reactions of Vehicle Markets to Fuel Price Changes

Changes in the price of gasoline induce new car buyers to alter their preferences for new cars. This reaction alters the mix of vehicles sold almost immediately. Automakers respond by altering the mix of vehicles they produce. If gasoline prices drop, the proportion of compact and subcompact cars purchased will decline, and soon after, production of such vehicles will decrease. If gasoline prices rise, sales of large and luxury cars and standard-size trucks will likely decline, and production cutbacks will follow. These effects have been studied by Carlson (see Sec. 3), and they are confirmed in a model presented below.

The reaction to rising gasoline prices is understood by automakers to be a search by consumers for greater fuel economy. This reaction sets in motion programs to recover sales and share of the larger, more profitable cars by improving their fuel economy, but this involves costly changes to the vehicles and to the engines in particular.[33] Consequently, automakers typically do not try seriously to develop and introduce more fuel-efficient vehicles until after the negative effects of a fuel price increase. This behavior has been shown by U.S. automakers throughout history.[33,34] The costs involved in developing new technology must be passed on to the consumer. Although the BLS new car price series does not reflect this (partly because it tries to hold constant the cost per unit of "quality" of the vehicle), the list price index used in this study does, as we will show below.

Sharp, sustained rises in gasoline prices place doubly negative pressures on new-vehicle manufacturers. First, the prices themselves, by making driving more costly, reduce the funds available for new cars and alter the pattern of purchases. Second, because of the costly changes to improve fuel efficiency, real list prices of new cars rise in an attempt to recover higher production costs, and sales decline even further. Because it takes a number of years to adopt significant technical changes, this process (which occurred from 1977 to 1983) causes several years of depressed new vehicle sales.

Low-income households, which are more often black and Hispanic, suffer from the side effects of this process. Specifically, although new car sales drop dramatically after a gasoline price rise, total vehicle holdings do not. This means that previous new-car buyers turn to the used-car market, thereby driving up the demand and price of used cars. Scrapping of used cars drops substantially, and the effects are most dramatic at the older end of the vehicle age distribution. Because published used-car prices are not available for the oldest cars, the magnitude of the real price rise for old cars could not be measured with the resources available for this study. However, it seems likely that this is an area where the costs of mobility for low-income households in general and minorities in particular rise dramatically.

These price increases are essentially imposed on low-income households by higher-income households shifting their demand. The low-income households do not get any technological improvement for the higher prices they have to pay, so the combined capital and operating costs of vehicular travel should rise more for low-income households than for other households. If this is so, the use of private vehicles for trips should drop more on average for low-income households than for all households and more for blacks and Hispanics than whites.

This is indeed what is indicated by a comparison of estimates from the 1977 and 1983 NPTS. As computations based on Table 1 can show, the 1977-83 rate of decline of private vehicle trips by low-income households was consistently greatest for low-income households. The argument that the combined vehicle and fuel costs increase at a greater rate for low-income households than for others after a fuel price shock is bolstered by the relative declines in use of transit and vehicles. Computations will show that, for middle- and upper-income households, the use of public transportation declined from 1977 to 1983 more than did the use of vehicles; but, for low-income households, vehicle use dropped sharply while public transportation use did not change. These patterns are consistent with a far more dramatic rise in costs of vehicle use for low-income households than for middle- to upper-income households.

Having described our understanding of the reactions by consumers and auto-makers to significant, sustained rises in gasoline price, we concede that this process is imperfectly modeled in MITRAM. Many of the steps are missing from the model. In some cases the asserted effects could not be estimated with available data, while in others there was simply not enough funding and staff time available to complete the work. The regressions presented below include several that are not in this version of the model. These are provided so that users wishing to modify the model will not have to reproduce work already done, as well as to illustrate that some of the steps asserted to exist have been verified. Additional variables for these equations are defined in Table 15.

4.7.2 New and Used Car Price Reactions to Gasoline Price and Related Technical Change (flow models)

Several new-car price regression equations were tested. The equation below is not the best one in terms of R^2, but it had the best properties in terms of plausible long-term price movements and integrability into the model. The regression equation included in MITRAM is

$$\begin{aligned} \Delta CMNCI(r83) = {} & \underset{(1.18)}{0.022} - \underset{(-2.39^*)}{1.78}\ \Delta VC_{-1} - \underset{(-1.50^*)}{0.39}\ \Delta MV_{-1} \\ & + \underset{(1.78^*)}{0.009}\ (NMPG_{-1} - NMPG_{-3}) \end{aligned} \tag{13}$$

R^2=0.56 $\quad\bar{R}^2$=0.46 $\quad F(4,18)$=8.18* $\quad$ D-W=1.41 $\quad$ N=22

The time period over which the regression is estimated is 1962-84. The constant term implies an upward bias to real car costs. However, this constant may represent the fact that rising regulatory costs for safety and emissions tended to increase relative car costs in the latter part of this period. Equation 16 (presented below), which was estimated only for the latter part of the period, supports this interpretation. Theoretically, one would expect a negative constant in this form of equation, with the negative constant being a measure of the long-term cost reductions that can be expected through technical changes in production.

The first two coefficients of Eq. 13 involve consumer demand, and the third involves the costs of product improving technical change. When **ΔVC** rises, the need for additional cars diminishes, lowering the demand curve and real prices. Longer vehicle life would contribute through this effect. If consumers plan trips more carefully and thereby decrease **ΔMV**, the need for additional vehicles again declines and the demand curve shifts downward, lowering real prices. When vehicle manufacturers find it necessary to improve fuel efficiency, production costs rise and manufacturers pass these costs through to the consumer in the form of higher vehicle prices.

The best fuel efficiency variable (**NMPG**) was one measuring an increment in fuel economy (mpg) rather than a percentage change, because there is a conceptual drawback to percentage change. As **NMPG** rises, the technical difficulty and costs of getting additional increments of fuel efficiency should rise. A percentage-change variable has the effect of implying that such costs decline; but the use of an **NMPG** increment is more

TABLE 15 Additional Variables for Fuel Economy Equations

Variable	Definition
CAFE	Fuel economy required by CAFE standards
ΔCAFE	$\ln(CAFE/CAFE_{-1})$
ΔCMNCI#	EPA size-class-specific, past-year, sales-weighted, base list-price change of the four most popular models sold in the class, equals $100\{[CMNCI(r83)/CMNCI(r83)_{-1}] - 1\}$
ΔCMNCI(r83)	Annual rate of change of price of a sales-weighted average new car, equals $\ln[CMNCI(r83)/CMNCI(r83)_{-1}]$
ΔG#	Percentage change in real gasoline price, equals $100\{[G(r83\$)/G(r83\$)_{-1}] - 1\}$
ΔG2	Two-year change in gasoline price, equals $\ln(G/G_{-2})$
INVB	Inventory build-up indicator, equals (MVP/MS)-1
ΔL>70	Past year's change in the fraction of new cars and light trucks sold that are large and luxury vehicles
ΔLG#	Percentage change in real gasoline price as it affects large cars, equals $L(100)\{[G(r83\$)/G(r83\$)_{-1}] - 1\}$, where L=1 for large cars, L=0 otherwise
LMvLxΔG2	Two-year change in gasoline price times one for large cars and minivans if ΔG2 is positive, zero otherwise
LRΔG(r)	Long-run gasoline price change, equals $-\{\ln[G(r)_{-1}/G(r)_{-7}]\}^{1/4}$
MS	U.S. car sales (thousands)[a]
ΔMS	Percentage change of all U.S. passenger car sales, equals $100\{(MS/MS_{-1}) - 1\}$
ΔMS(ln)	$\ln(MS/MS_{-1})$
MSI	Imported motor vehicle sales
ΔMSI	Percentage change of imported passenger cars sold in the U.S.A., equals $100\{(MSI/MSI_{-1})-1\}$
MVP	Motor vehicle production (thousands)[a]
ΔMVP	Change in motor vehicle production, equals $\ln(MVP/MVP_{-1})$
ΔMVS	Change in motor vehicle sales, equals $\ln(MS/MS_{-1})$
ΔNMPG	Annual increment in fuel economy of fleet of passenger cars sold (mpg), equals $NMPG - NMPG_{-1}$
POSΔNMPG	$(NMPG_{-1} - NMPG_{-3})$ if this quantity is positive, zero otherwise
ΔRGLN	Percentage increase in new car cost due to regulation for safety and emissions as measured by BLS,[b] equals 100(regulatory cost per car/list price of car)
S	Cars scrapped (thousands)[a]
Sc&CΔG2	Two-year change in gasoline price times one for subcompact and compact passenger vehicles, zero otherwise
StTkΔG2	Two-year change in gasoline price times one for standard size trucks, zero otherwise
U	Unemployment rate, expressed as a percentage
ΔVC	Annual rate of change of vehicles per capita, equals $\ln(VC/VC_{-1})$
VPC	Domestic production of passenger cars and light trucks on a per-capita basis

TABLE 15 (Cont'd)

Variable	Definition
W	Workers in the U.S. labor force (thousands)
WCr%	Labor force participants per capita, expressed as percentage (r is racial identifier, W = white, B = black)
Y	Real U.S. median income (1983 dollars)[c]
YC	Real personal income per capita
ΔYC	$\ln(YC/YC_{-1})$
Yr	Year

[a]From Ref. 16 (1987).

[b]From Ref. 16 (1986).

[c]From Ref. 12.

or less neutral. The use of a two-year increment in mpg (POSΔNMPG) resulted in a statistically significant coefficient. Tests of two-year rates of change for ΔVC and ΔV caused declines in the t-statistics of the coefficients. An equation testing the hypothesis that only positive changes in fuel efficiency cause increases in cost was successful, but not so much better that it was used in MITRAM. The typical change in NMPG is, in any case, upward. Using POSΔNMPG in Eq. 13, one obtains:

$$\Delta CMNCI(r83) = \underset{(1.18)}{0.018} - \underset{(-2.43^*)}{1.75\ \Delta VC_{-1}} - \underset{(-1.48^*\ )}{0.38\ \Delta MV_{-1}} + \underset{(1.98^*)}{0.011\ POS\Delta NMPG} \qquad (14)$$

R^2=0.58 $\bar{R}^2$=0.48 F(4,18)=8.67* D-W=1.42 N=22

In MITRAM, changes in used car prices are a simple function of changes in new car prices. The theoretical reason that the two should be linked is that new and used cars can readily substitute for one another. The estimated relationship is

$$\ln(CUCI/CUCI_{-2}) = 0.03 + 0.92\ CMNCI/CMNCI_{-2} \qquad (15)$$

R^2=0.58 $\bar{R}^2$=0.54 F(2,21)=30.01* D-W=1.04* N=23

In addition to the aggregate new car price equation included in MITRAM (Eq. 13), a regression equation was constructed to give some detail about price increases for particular car sizes. This proved to be more detailed than necessary for MITRAM. The regression results, however, do reinforce the argument that fuel efficiency improvements lead to list price increases, supporting the results in Eq. 13. The variables used in the class-specific new car price regression were defined slightly differently than has been done for most of the flow models; growth rates were defined as percentages (see Table 15). The regression results are:

$$\begin{aligned}\Delta CMNCI\# = & -3.29 + 0.24\ \Delta G\#_{-1} - 0.37\ \Delta LG\#_{-1} + 0.91\ \Delta RGLN_{-1} \\ & \quad (-2.14^*) \quad (4.08^*) \qquad (-3.31^*) \qquad (2.16^*) \\ & + 8.43\ \Delta NMPG_{-1} + 0.08\ (\Delta MS_{-1} + \Delta MS_{-2}) \\ & \quad (4.64^*) \qquad\qquad (1.47^*) \\ & - 0.07\ (\Delta MSI_{-1} + \Delta MSI_{-2}) \\ & \quad (-1.18)\end{aligned} \tag{16}$$

$R^2=0.47$ $\bar{R}^2=0.41$ $F(7,58)=8.44^*$ D-W=2.11 N=65

This equation is a combined time-series/cross-sectional model for five car classes and 13 years (1974-1986), resulting in 65 observations. The equation was confined to this period because this was the interval for which we had compiled our list-price data base. None of the independent variables are class-specific; national average values are simply repeated five times for each car size class. The new car prices, which are class-specific, rely completely on the list price values compiled for this study and do not use any car price information from government price series. Developing this final equation involved constructing five separate equations for each car size class, with separate examination of coefficients for each class. The large-car class reactions to gasoline price increases were clearly different than for other size classes, leading to the construction of the multiplicative dummy variable **LG**.

The equation has a gasoline-cost coefficient with a positive sign (except for large cars) and includes effects of car sales. The car sales coefficients support the argument that increased demand for cars is followed by rising car prices, while increasing competition from imports holds prices down. The latter result, however, is not supported by a statistically significant coefficient. Several variants of the import variable (using multiplicative dummy variables to isolate import competition to smaller size classes, where the competition is most obviously direct) were tested in search of a statistically significant relationship. None of the variants were statistically significant. If the car sales variables (the **ΔMS**- and **ΔMSI**-based variables) are taken as the only causes of new car price change, the coefficients estimated have the opposite sign and the R^2 value is only 0.08.

The two gasoline price coefficients support the argument that a gasoline price increase shifts demand away from large cars and possibly increases costs of vehicle production. When estimated separately as causes of real new car list price change, the gasoline price coefficients are essentially unchanged and they each remain significant. The R^2 value of such an equation is 0.24. As in Eq. 13, the constant term in such an equation is positive, implying that other factors were operating to cause rising list prices from 1974 to 1986.

The two technological change coefficients (of $\Delta NMPG_{-1}$ and $\Delta RGLN_{-1}$) measuring the costs of improving vehicle safety, emissions characteristics, and fuel economy indicate that such technical change is costly, forcing list price increases. When the two technical change variables are estimated separately, the coefficients are essentially unchanged and they each remain significant. The R^2 value of such an equation is 0.28. The constant term in such an equation is negative, as it is in the full equation. This is what one would expect since, all things being equal, technical change would reduce costs of production, and thereby list prices, over time.

These results support the argument that technical change which improves safety, emissions, or fuel efficiency is costly and that it has more to do with variation in list prices than does international competition. They also support the argument that technical change that reduces production costs does take place steadily enough over time to appear as a negative constant in a rate-of-price-change equation. Working in the opposite direction are technical changes needed to improve safety, emissions, and fuel economy. If the constant term and the technical change variables measure the costs of technical change, as argued here, technical change is responsible for most of the price variation explained by this equation.

Costs of product improvements, if high, can contribute to a decline in sales of new automobiles and, by the chain of events discussed earlier, can probably cause sharp increases in the cost of mobility for low-income households in general and minorities in particular. Santini has argued that the cost increases from fuel-efficiency-enhancing technical change typically lead to declines in vehicle sales in the short-run, but have the effect of allowing greater economic growth over the longer term.[35] The highest costs of safety and emissions regulation and the most rapid increases in fuel economy both occurred within two years, in the midst of a depression in the auto industry and following the single most severe rise in oil prices in the twentieth century. These equations support the view that the imposition of regulatory costs and the simultaneous fuel price increases were a serious problem, contributing to the automobile industry's depression in the early 1980s.[36] Further, according to the arguments presented here, they probably also contributed to the effects in the used car market that led to the uniquely sharp loss of vehicular mobility that occurred between 1977 and 1983 for low-income and minority households.

4.7.3 Vehicle Sales and Holding: Reactions to Changes in Vehicle and Fuel Prices

It has been argued that new vehicle price rises contribute to a chain of events that decrease demand for new cars and increase demand for used cars. MITRAM does not directly model these effects; instead, it directly estimates net demand for all cars. No estimates of used car demand have been constructed or incorporated into the model at this time. Wildhorn et al. (Table 4, #11) estimated used car demand, indicating that a new car price increase indirectly causes an increase in demand for used cars. The positive coefficient of used car demand as a function of new car price is more than twice as large as the negative coefficient estimating the effect of used car prices.

In examining models for possible incorporation into MITRAM, we explored a new car demand equation that tends to corroborate the general findings of Carlson's new car demand model disaggregated by size class (Table 4, #1). It was constructed in the same fashion as Eq. 16, with slight differences in the time interval and the new vehicle models. Using the data for Eq. 16 in a combined time-series/cross-sectional equation with five size classes showed that the coefficients measuring the reaction of class sales to class-specific prices could not be statistically distinguished from one another. Thus, a price index for all vehicles was about as good as one for the specific class being estimated. (This is consistent with Carlson's results. Carlson obtained negative coefficients that were very similar to one another, ranging from -0.267 for subcompacts to -0.422 for full size cars; the coefficient for compacts was an exception, at -0.677.) Using an aggregate new car price index allowed us to extend our series back in time and to more accurately incorporate the full effect of the 1973-74 oil price shock.

Carlson also estimated the effects of income. Like vehicle price, his income coefficients were very similar for four of the five car classes, ranging from 0.502 for intermediates to 0.881 for compacts. No income coefficient entered into Carlson's full-size-car demand equation. In the equation presented below, a single income coefficient for all vehicle size classes is estimated.

Because of the increasing popularity of light trucks as substitutes for cars and of minivans for large cars, we felt that demand for passenger vehicles could no longer be accurately depicted by modeling cars separately from trucks. Consequently, we added trucks to our classes of vehicle demand. The equation also includes both domestic and imported vehicles, so it is a U.S. passenger vehicle demand model. Trucks were added to standard industry classes.[14,16] Minivan and other truck sales by size class were obtained from Hu and Williams.[15] For this equation,

- Small light trucks were treated as cheap new cars and were added to the subcompact car class;
- Minivans and large passenger vans were considered to be substitutes for large passenger cars and were added to that class; and
- Standard-size light pickup trucks and nonpassenger large vans were treated as a separate class of vehicle.

The estimated equation is:

$$\Delta MS(\ln) = \underset{(1.12)}{0.040} + \underset{(1.43^*)}{1.74\ \Delta YC} - \underset{(-2.83^*)}{2.45\ \Delta YC_{-1}} - \underset{(-1.54^*)}{0.96\ \Delta CMNCI} \tag{17}$$

$$- \underset{(-2.98^*)}{0.65\ \Delta G2} + \underset{(2.91^*)}{0.54\ Sc\&C\Delta G2} - \underset{(-2.33^*)}{0.61\ LMvLx\Delta G2} - \underset{(-1.83^*)}{0.38\ StTk\Delta G2}$$

$R^2=0.65$ $\bar{R}^2=0.61$ $F(8,62)=16.50^*$ D-W=2.36 N=70

This equation was estimated for 1972-1985. It included five vehicle classes at 14 observations each, for a total of 70 observations. The constant term implies 4% per year growth in new car sales. The effects of expanding employment per person were tested but were not significant. Like Carlson, we found that the variations by vehicle size in reaction to real gasoline price increases were dramatic. The coefficient for intermediate-size cars in our equation was -0.65, about the same as Carlson's. For large cars and minivans, our net real gasoline price coefficient was -1.26, about three times Carlson's coefficients. For subcompacts and compacts our net coefficient was only slightly negative, at -0.11, whereas Carlson's coefficients were positive. Our net coefficient for standard size trucks was -1.03 (Carlson did not estimate a coefficient for trucks). In relative terms and by vehicle class class, our coefficients were similar to those of Carlson but consistently larger. Perhaps estimation with the method of seemingly unrelated regressions would eliminate some of the differences. Carlson used a quarterly model ending in 1978, whereas we used annual data incorporating another severe oil price shock. Also, by using a two-year increase in gasoline price, we may be capturing delayed consumer reaction to sustained gasoline price increases, while Carlson captured shorter-term responses. In any case, the similarities of the results are more striking than the differences. The primary conclusion is that gasoline price increases have asymmetrical effects on various vehicle size classes, with larger vehicles affected by the most severe declines in consumer demand.

Although used car demand was not estimated, preliminary scrappage equations were estimated. The equations were stock models estimating total vehicles scrapped rather than rate of change of scrapping. The first scrappage equation is:

$$\underset{(-0.07)}{S = -105} + \underset{(4.90*)}{0.70\ MS_{-1}} + \underset{(1.85*)}{8.26\ G} \tag{18}$$

R^2=0.65 $\bar{R}^2$=0.56 F(3,13)=12.26* D-W=1.71 N=16

This equation is estimated for the period 1970-1985 and confirms that new car sales are positively associated with car scrapping. A reduction in new car sales would lead to a reduction in scrapping, which would translate into an increased demand for used cars. A second implication is that gasoline price increases must have a dual effect. The simple relationship estimated here implies an immediate increase in scrapping when gasoline prices rise. More investigation would probably confirm that this is a quick reaction in which large, low-mpg cars are scrapped. The longer-term lagged effects of a gasoline price increase, as shown in Eqs. 16 and 17, are to increase vehicle prices and reduce vehicle consumption. Further study would probably show increased demand for more fuel-efficient used cars. These effects seem to be apparent in used car price data that we have collected but not yet analyzed.

A second scrappage model, in which multicollinearity effects of three variables eliminate the statistical significance of the car sales variable, is

$$S = \underset{(-2.89*)}{-15685} + \underset{(2.86*)}{41.4\ G} + \underset{(4.16*)}{1.02\ Y} - \underset{(-2.48*)}{5253\ \Delta CUCI(r83)} - \underset{(-1.57*)}{0.064\ W} \tag{19}$$

R^2=0.79 $\bar{R}^2$=0.69 F(5,11)=10.61* D-W=2.86 N=16

This equation implies that a rise in income causes replacement of used cars with new cars, leading to increased scrapping. When the cost of used cars rises, their higher value makes it more economical to sell them than scrap them. After income and used car price effects are taken into account, the more workers there are, the more vehicles are needed to get to work, and the need for those additional vehicles reduces the scrapping rate.

4.7.4 Vehicle Sales and Employment

The specification of the design of MITRAM as a component of a larger modeling effort (an income projection model is being designed by another contractor) conducted under the Office of Minority Economic Impact required that minority and majority income and employment be exogenous inputs to the model. These conditions made the construction of MITRAM somewhat simpler than if vehicle sales and production effects on minority employment had been a required component. Blacks have historically enjoyed better employment opportunities in vehicle manufacturing than in many other sectors of the economy. Thus, in principle there would be good reason to construct an employment and income feedback loop in the model, under which vehicle sales would affect black income and, ultimately, the share of income devoted to gasoline consumption and public transportation spending. A vehicle production model was estimated that would be capable of simulating the production response to vehicle sales changes.

A resulting production-change equation is:

$$\underset{(-3.59^{*})}{\Delta MVP = -0.033} + \underset{(18.08^{*})}{1.05\ \Delta MVS} - \underset{(-3.65^{*})}{0.19\ \Delta MVS_{-1}} - \underset{(-5.85^{*})}{1.42\ INVB_{-1}} \qquad (20)$$

R^2=0.98 $\bar{R}^2$=0.97 F(4,12)=230.52* D-W=2.05 N=16

This equation implies that current motor vehicle sales are the dominant cause of production changes. Inventory adjustments made necessary by divergence of production and sales in the prior year have a significant effect on production in the current year. A good sales growth rate tends to be followed by a lower production growth rate in the next year, adding a long-term stability to the process of sales and production adjustment.

The employment equation currently used in MITRAM is a crude equation designed to "close" the model and make it operable. If, in the future, estimates of majority and minority income from others become available and they include estimates of employment levels, MITRAM could easily be adapted to use these values. The employment estimates in MITRAM now rely exclusively on exogenously specified unemployment rates and a trend. The exogenous rates used in the model have typically been projections from a Data Resources, Inc. (DRI) macromodel, with tailoring of the projection to the needs of the overall research effort.

The simple employment-per-person equations used in MITRAM were constructed by collecting data on white and black employment and population from U.S. Statistical Abstracts.[12] The series in these tables were not continuous, so the Durbin-Watson time-series statistic is not necessarily valid. Because the construction of employment estimates was specifically delegated to others, only limited time was spent on these regressions. The years in the equation for whites are 1960, 1965, 1970, 1975, and 1978-1985. The years in the equation for blacks are 1973, 1975, and 1978-1985. For whites:

$$WCW\% = \underset{(4.65^*)}{12.25} + \underset{(10.75^*)}{0.44\ Yr} - \underset{(-2.23^*)}{0.42\ U} \tag{21}$$

$R^2=0.95$ $\bar{R}^2=0.93$ $F(3,8)=70.52^*$ $D\text{-}W=1.76$ $N=11$

For blacks:

$$WCB\% = \underset{(4.65^*)}{14.06} + \underset{(15.10^*)}{0.33\ Yr} - \underset{(-15.44^*)}{0.84\ U}$$

$R^2=0.98$ $\bar{R}^2=0.97$ $F(3,7)=154.90^*$ $D\text{-}W=2.41$ $N=10$

According to these two equations, black employment rates are twice as sensitive to changes in national unemployment as whites, and the rate of growth of employment per capita for blacks is only 75% that of whites over the estimated interval. It should be noted that the current version of MITRAM extrapolates these trends into the future.

While we have not explicitly accounted for the entrance of women into the labor force, it is implicitly included in the sense that number of workers per household is a key variable in many of the equations in the model. Further, the simple trend used here incorporates the recent effects of women entering the labor force. We have not tested the implicit assumption that the effect of a job on vehicle holding is the same for men and women. Our failure to estimate the contribution of women in the number of workers per capita is partly because the employment equation is not our responsibility in the overall project.

A probable missing link in MITRAM is that between new vehicle sales, vehicle production, and employment levels. The need for such a link is supported by a simple regression of the U.S. civilian unemployment rate on per-capita domestic production of passenger cars and light trucks.

$$U = \underset{(7.15^*)}{11.35} - \underset{(-2.86^*)}{98.96\ VPC} \tag{22}$$

$R^2=0.34$ $\bar{R}^2=0.25$ $F(2,16)=8.15^*$ $D\text{-}W=1.22$ $N=18$

This equation is estimated over the period 1970-87. If one assumes that the direction of causality is predominantly from vehicle production to employment rather than the reverse, this equation supports the possibility that variations in vehicle production account for about one-quarter of the variation in U.S. unemployment. Because causality is bidirectional, the share of U.S. unemployment variation caused by the direct and indirect effects of vehicle production is somewhat lower than implied by this equation.

Nevertheless, for a single sector of the economy, the implied effects are large. Were MITRAM to include endogenous determination of employment, and thereby income, as a function of vehicle production, it would partially replace exogenous sources such as the DRI macromodel.

4.7.5 Determinants of Fuel Efficiency

New Car Fuel Economy

Perhaps the most important aspect of MITRAM is its ability to project the fuel efficiency of new vehicles as a short- or long-term reaction to real gasoline price increases. A basic property of the new car fuel efficiency model is that it simulates both easy, short-run improvements in fuel efficiency and technically difficult, long-run improvements. Easy improvements would include resetting or substituting fuel delivery systems (carburetors or fuel injectors) and transmissions and gear ratios. Long-term improvements would involve redesign of entire vehicle and engine systems. Such a redesign takes a little more than half a decade to enter initial production. If real gasoline prices rise sharply, such technically difficult projects will be put into motion by automakers. If prices stay high, the work will continue. If prices do not drop before manufacturing facilities are set up, these projects will be brought into production.

Other side effects of gasoline price increases during the 1970s and early 1980s were the use of government regulation to promote fuel efficiency and the selection of fewer large vehicles by consumers. The former (i.e., the CAFE standards) ostensibly required sales-weighted increases in fuel economy by each U.S. vehicle manufacturer. The latter was a manifestation of the gasoline-price-induced changes in size preferences evident in the coefficients estimated for the vehicle-size-specific sales equation (Eq. 17).

These effects are captured in the **NMPG** equation, which is:

$$\begin{aligned} \Delta NMPG = \underset{(0.84)}{0.005} + \underset{(4.29^*)}{0.308}\, \Delta G(r)_{-1} - \underset{(-1.69^*)}{0.321}\, \Delta L{>}70 + \underset{(1.58^*)}{0.354}\, \Delta CAFE \\ + \underset{(2.56^*)}{0.034}\, LR\Delta G(r) \end{aligned} \tag{23}$$

$R^2=0.73$ $\quad$ $\bar{R}^2=0.68$ $\quad$ $F(5,27)=18.10^*$ $\quad$ D-W=1.95 $\quad$ N=32

MITRAM projects new car fuel economy and translates it into fleet fuel economy to account for the lagged introduction of new cars into the fleet. The estimates are adjusted downward to reflect actual on-road driving experience.

On-Road Fleet Fuel Economy

Fuel efficiency on the road is less than that measured in vehicle tests as conducted by EPA in the 1970s[37,38] and by organizations such as the United States Auto Club before that. In this research, we have used a statistical series for rated new car mpg (NMPG) and have applied a race-specific adjustment to account for the fact that on-road fuel economy is less than rated new car fuel economy. Although new car fuel economy can (and did) rise dramatically in a short time, rises in fleet fuel economy are limited because only a small proportion of the fleet is replaced by new cars each year. Consequently, when new car fuel economy moves upward, the ratio of fleet fuel economy to new car fuel economy drops. This happened for a number of years in the 1970s and early 1980s. Higher-fuel-economy vehicles replace other vehicles that are scrapped, but as these vehicles age, they represent a smaller and smaller proportion of the fleet as they themselves are scrapped. Thus, the relative effect of a given model-year group on the fleet will decline each year, until that group is such a small part of the fleet that it has no effect.

To model the difference between the black and the white vehicle fleets, we had to take into account the fact that blacks own significantly older cars than whites. Because whites generally have higher incomes and purchase more new cars, they will be first to realize a significant gain when the rated fuel economy of new cars increases significantly. Then, as higher-income whites place cars on the used car market, lower-income blacks will have the opportunity to increase the fuel economy of their vehicles. The effect is that the distribution of vehicles by age of vehicle will be significantly different for blacks and whites (as it would also be for high-income white households compared to low-income white households).

A model such as Sweeney's (see Table 7, #7), which accounts for the effects of variation of scrapping rates on vehicle survival, is one possible form of model that would show how improvements in new car fuel economy reach the fleet. In our case, however, we would have to resolve additional complications: the filtering of improvements from new car purchasers to middle-income households through the used car market and the filtering of better qualities in younger used cars to low-income households. Such an ideal model would incorporate detailed equations describing the interactions among new car sales, time to resale of cars purchased new, and annually varying scrappage rates of old cars by age, after accounting for gasoline prices, car prices, household income, and level of employment. The approach we have chosen is considerably simpler. We evade the problem of modeling transactions in the used car market by simulating an age distribution that will vary as household income and car costs vary. We create a model which simulates that high-income households will have a fleet with very young vehicle ages, while the fleet held by a group of low-income households will include many old cars.

We take advantage of the fact that the Chi-square distribution is very peaked for low values of the mean of the distribution but flattens out as the size of the mean increases. Because the mean of a Chi-square distribution can be used to generate the distribution, we used an estimate of the mean age of cars held by blacks and whites to construct the Chi-square probability distribution of holding a vehicle as a function of the age of the vehicle in model years (because new car mpg ratings are by model year).

Although the Chi-square distribution with a low mean has initial low probability values, these rise very sharply. The distribution can approximate that of cars held by age, including new cars, if one takes the time in the initial year as being very early in the calendar year, so that only a few months of new car sales have taken place. Also, the significant minority of cars purchased for business fleets are very young on average, so that even whites are second in line to fleet purchasers in terms of age of vehicles owned. By accounting for these relationships, the number of new-model-year cars owned early in the year can be well under half of those one year old. Accounting for first purchase by fleets, whites may actually own fewer cars one and two model years old than those three and four model years old. This is in fact what our model simulates.[1] Whites are simulated on average to own about the same proportion of cars in the third and fourth model year, but about 20% less cars in the second model year. For blacks the highest proportion of vehicles in their fleet were six model years old, so the ownership of older used vehicles was simulated appropriately.

We confirmed this effect by comparing the 1985 age distribution of the complete (business and personal) car fleet, based on R.L. Polk registration data, with the 1985 RTECS age distribution for households (personal vehicles). The differences for the zero-model-year shares of the fleet, which consisted of 1986 model year cars, were generally consistent with this argument. The zero model year represented 6.0% of all cars, but only 1.3% of personal cars. Nine percent of all cars were one model year old (1985 model year), but only 7% of personal cars were this age. The MITRAM estimates for whites for these years are 1.5% and 5.5%.

This check did reveal that the MITRAM method is flawed following a car sales collapse. MITRAM estimates too high a share for the poor sales years of 1979 to 1983 and thus overestimates the rate at which gains in fuel economy enter the fleet. Overall, however, MITRAM tends to underestimate the shares of vehicles owned that are four or fewer years old by about 15%. This implies that much of the variation in shares of vehicles held of a given model year is related to the number of vehicles originally sold in that model year. A 72-observation regression comparing MITRAM share estimates for vehicles of a given mean age to those in the 1983 NPTS sample (Ref. 17, Table 4-15) indicated that the MITRAM method captured 44% of the variation and that the mean share estimates were within 7% of the NPTS values.

The first step in the process of developing the Chi-square models of the age distribution of household fleets is to estimate a mean age of the fleets held by majority and minority groups. The three groups analyzed in this report have different income levels and would therefore be expected to own cars of different ages, with the oldest cars being owned by the lowest income group. Since this portion of the work was completed after review of the model, only limited funds and time were available for revision. Accordingly, we have only used previously estimated group means from three of our major data bases rather than estimating age-of-vehicle-owned as a function of household income for the thousands of available observations. The means used were compiled from the 1977 NPTS, the 1983 NPTS, and the 1985 RTECS.

A mean vehicle age was compiled for whites, blacks, and Hispanics for each of these three years. National estimates of the median income (in 1986 dollars) of white, black, and Hispanic households for these years were obtained from the 1988 Statistical Abstract, as were national estimates of the used car price index (**CUCI**). This index was deflated by the consumer price index to obtain a real used car price index, **CUCI(r78)**, based on the year 1978. These statistics enabled us to run three-observation cross-sectional regressions for each year and three-observation time-series regressions for each of the three household classes; combining these allowed us to run a nine-observation regression. The results are presented in Table 16. The independent variable in these regressions is the square root of the quantity **CUCI(r78)** divided by median household income. The dependent variable is mean age of the vehicles in the household's fleet, measured in years. The expectation was that higher income would lower the age of the vehicles owned. Higher vehicle purchase costs (**CUCI**) were expected to cause households to buy older cars to minimize vehicle cost. The use of the square root of **CUCI** over income as an independent variable was selected after examining other formulations. The logarithm of **CUCI** over income gave apparently equal statistical results, but the estimates of ages of vehicles owned by income group were less plausible for high and low incomes.

In view of the fact that there were only three observations in the three cross-sectional and three time-series regressions, a lack of statistical significance along with a high R^2 value was expected. In a statistical sense, the time-series regressions were consistently better than the cross-sectional regressions. For whites and blacks, the coefficients in the time-series models were statistically significant. However, the constant terms in the time-series models were negative, implying that cars with a negative age would be owned by highest-income households. The cross-sectional models, on the other hand, implied that even high-income households would not own fleets of less than about five years average age. The combined time-series/cross-sectional model was better, but still implied that highest income households would not own fleets of cars averaging less than four years of age.

The small sample tests supported the view that the relationships between income, vehicle cost, and vehicle age were not, to any great degree, a function of minority status. Consequently, a time series for all U.S. households was estimated for 1970-1986 (fourth set of entries, Table 16). This seventeen-observation time series had the same drawback as the three-observation time series: a negative constant term. A regression forced through the origin was run to create an estimate that would not allow ownership of a vehicle fleet with a negative age. Holding **CUCI** equal to 100, the resulting values were checked over a range of incomes from \$5,000 (age = 14.1 years) to \$250,000 (age = 2.0 years). We concluded that this no-constant equation gave satisfactory estimates.

One point that emerged from constructing the estimates in Table 16 was that the R^2 values were higher for time series. In the cross-sectional model, only income contributed to the explanation of vehicle age, but in the time-series model, both income and used car costs contributed. As a check to see if used car costs offered more explanatory power, regressions using only the square root of the inverse of income or only the square root of **CUCI(r78)** were compared to the regression in which a composite form of these two was the independent variable (Table 17). For the cases where all three forms of the regression were constructed, it was almost always true that used car price equations had higher R^2 values than those using only income. Looked at another way, when the "composite used car and income" variable ("combined" column of Table 17) was substituted for an "income only" variable (first column of Table 17), the increase in R^2 was typically greater than the R^2 value for income alone. Clearly, the cost of vehicles, as measured by the used car price index, has a great deal to do with the age of vehicles that consumers are willing to hold.

TABLE 16 **Estimated Coefficients for Models of Average Vehicle Age**[a]

Model	Constant (t-value)	Coefficient (t-value)	$R^2/\bar{R}^2$ (F-value)
Cross-sectional (n=3) (white, black, and Hispanic)			
1977	5.39 (2.71)	20.82 (0.78)	0.38/0.25 (0.60)
1983	5.71 (1.65)	34.57 (0.81)	0.40/0.20 (0.57)
1985	5.87 (4.99)	30.64 (2.12)	0.82/0.64 (4.51)
Time-series (n=3) (1977, 1983, and 1985)			
White	-8.68 (-16.1*)	238.83 (29.90*)	1.00/1.00 (894.1*)
Black	-9.35 (-4.14)	196.31 (7.69*)	0.98/0.97 (59.16*)
Hispanic	-5.76 (-0.89)	176.58 (2.19)	0.83/0.65 (4.78)
Combined (n=9)	3.72 (1.83)	53.5 (2.09*)	0.38/0.30 (4.35*)
Time-series, 1970-86 (n=17)			
National averages	-2.94 (-2.94*)	145.09 (8.68*)	0.83/0.82 (75.12*)
National averages (no constant)	-- (--)	100.04 (70.82*)	0.75/0.74 (45.68*)

[a]Asterisks indicate statistically significant values.

Given the limited information available and the size of the standard errors involved, there appears to be no basis for assuming that whites, blacks, or Hispanics differ in their behavior with respect to age of vehicles owned. Such a conclusion would probably not hold up if all household observations in the data bases were used. Hispanics owned older vehicles than blacks even though they had higher incomes, and both owned older vehicles than whites. The widest actual and predicted differences between whites and minorities were in 1983, which was the worst economic year of the three. At that time the sample vehicle mean ages were 7.84 years for whites, 8.57 for blacks, and 9.08 for Hispanics.

TABLE 17 Values of R^2 for Models of Average Vehicle Age that Include Car Price

Model	Income-Based	Used Car Index-Based	Combined	Incremental $(\Delta R^2)^a$
Cross-sectional (n=3) (white, black, and Hispanic)				
1977	0.38	--	0.38	--
1983	0.40	--	0.40	--
1985	0.82	--	0.82	--
Time-series (n=3) (1977, 1983, and 1985)				
White	0.43	0.88	1.00	0.57
Black	0.34	0.80	0.98	0.64
Hispanic	1.00	0.60	0.83	-0.17
Combined (n=9)	0.19	0.59	0.38	0.19
Time-series, 1970-86 (n=17)				
National averages	0.36	0.72	0.78	0.42
National averages (no constant)	0.16	0.60	0.70	0.54

[a]Equals "combined" value minus "income-based" value.

Having obtained an estimate of the average age of a vehicle, our model then uses that estimate as the mean value of a Chi-square distribution. For each year (denoted by n) of age of a vehicle from zero to twenty-five years, the Chi-square distribution is used to estimate a proportion of vehicles owned.

The Chi-square distribution requires that a gamma function (Γ) be estimated.[39] The gamma function is itself a function of half of the mean age of the vehicle fleet. In MITRAM, we used **VAW** to denote mean vehicle age for whites and **VAB** for blacks. This is generalized to **VAr**, where r is the race identifier. For proposes of estimating the gamma function, we set the term a = **VAr**/2 and used Stirling's asymptotic approximation of gamma.[40]

$$\Gamma(a) \approx a^a e^{-a} \sqrt{\frac{2\pi}{a}} \left[1 + \frac{1}{12a} + \frac{1}{288\ a^2} - \frac{139}{51{,}840\ a^3} - \frac{571}{2{,}488{,}320\ a^4} + \ldots\right] \quad (24)$$

Once gamma has been estimated, it can be substituted into the Chi-square equation, which is then separately estimated for each of n (25) years to determine the proportion of the fleet aged n years, which we term **PPNr(n)**.

$$PPNr(n) = \frac{n^{(VAr-2)/2}\ e^{-n/2}}{2^{VAr/2}\ \Gamma(VAr/2)} = \frac{n^{(2a-2)/2}\ e^{-n/2}}{2^{a}\ \Gamma(a)} \tag{25}$$

The adjustment of share estimates according to the mean age of the vehicle was checked by comparing this estimate to the 72 observations of yearly shares from the 1983 NPTS. This involved eight vehicle fleets with eight different mean ages. Eight Chi-square distributions that estimated shares as a function of age were generated. As discussed earlier, the Chi-square model explained 44% of the variation of the eight NPTS sample fleets. When three different single Chi-square distributions were separately tested, the lowest cases explained only 3-10% of the variation, and the highest explained 30%. The distribution with the youngest age gave the best results. The age adjustment discussed later in this section consistently gave improved results.

The rated fleet fuel economy is estimated by multiplying the proportion of vehicles of a certain age [**PPNr(n)**] by the rated new car fuel economy of vehicles of that age [**NMPG(n)**] for each year and then summing over all years. To obtain actual on-road fuel economy, which is less than fleet fuel economy, we use ratios that we constructed for each household type from the 1985 RTECS.

Using assumptions and judgement as necessary, EPA ratings by model were cross-indexed (from data bases supplied by Oak Ridge National Laboratory) to each household in the 1985 RTECS file -- a tedious and time-consuming task. The mean EPA ratings were then compared to the recorded household trip distances and fuel consumption data to estimate both EPA-rated and on-road mpg. According to those estimates, blacks surveyed for the RTECS had about 6% lower on-road mileage than whites, with about 90% of this difference being a result of ownership of inherently lower-mpg vehicles. The rest of the difference could be attributable to driving in more congested conditions and the condition of the vehicle. The ratio between the EPA rating for whites and the on-road performance of their vehicles was estimated to be 0.805; for blacks the ratio was 0.799, and for Hispanics, 0.788. On-road fuel economy for whites (**OFFEW**) and for blacks (**OFFEB**) is estimated in MITRAM as follows:

$$OFFEW = 0.805 \sum_{n=0}^{25} PPNW(n) \cdot NMPG(n) \tag{26}$$

$$OFFEB = 0.799 \sum_{n=0}^{25} PPNB(n) \cdot NMPG(n) \tag{27}$$

5 CONCLUSIONS

This report documents research to estimate coefficients for a computer model, MITRAM, that compares the share of income spent on transportation by minority populations to that spent by the majority. The estimation process is quite complex, and the data needed for many of the aspects of the process are not in forms that allow easy use. We hope that this description of our efforts will provide useful information, allowing interested parties to make improved judgments about how tax and subsidy policies could differentially affect minority and poor populations.

Aside from its potential to estimate minority transportation expenditure shares, MITRAM contains features that we believe make it uniquely valuable for assessing long-range effects of oil and gasoline taxes or fuel economy standards. MITRAM may be the first model to simulate the technological reactions that occur several years after a gasoline price change. The fact that the auto industry takes a relatively long time to fully react to fuel price changes has been documented statistically[41] and illustrated graphically.[42] Gately and Rappoport[43] have recently shown a long-term macroeconomic response to oil price changes that has much the same time lag as that shown by Eq. 23 of this report and by the equations of Santini.[41] The fact that MITRAM predicts long-term responses is a contribution that should prove useful for energy policy analysis. Further, the similar lag in macroeconomic and transportation-sector technology effects suggests the possibility of a systematic linkage between these responses, as has been previously argued.[33,44]

Policies that could be addressed by MITRAM are fuel efficiency standards, fuel taxes, the value of increased investment in public transit, and how these three differentially affect low-income minorities. Our research implies that at least one analyst[32] has erred in asserting that fuel taxes would not be regressive. Other analysts, such as Bleviss,[45] have argued for strict fuel economy standards to force technological change, without considering the possibility that the proposed change might have negative effects. One such effect -- the escalation first of new car costs, then of used car costs -- can be addressed with judicious modifications of MITRAM.[1] Although MITRAM may still be too crude to answer questions such as which policy is best or how much of each policy is best, it probably can determine how much of a mpg-enhancing technical change or a gasoline tax increase is too much and shed light on the trade-offs between short-term losses and long-term gains. Ross[46] has recognized that it is necessary to select public policies on transportation fuels which "are not economically severe and which do not severely intrude on the private decision making process" while also recognizing that energy demand *is* a matter for rational public policy, rather than "simply being . . . the consequence of a particular fuel-price elasticity -- if one looks ahead far enough in the future so that there is time to make decisions (at normal replacement times) about the capital equipment involved." MITRAM is designed to allow a "look ahead" by modeling the process of replacing capital equipment (vehicles) and simulating how the replacement effects trickle down to lower-income minority households.

We have not had enough time to analyze, test, and recalibrate the MITRAM model to allow it to give estimates of transportation spending for various income groups. Nor can we claim to have yet configured the model so that the effects of higher- or lower-than-normal incomes for blacks or whites can be accurately modeled. As the discussion in the body of this report should show, there are a number of effects that we think can be modeled, but we have not had time to do so. We can say that the addition of the public transportation relationships to the model and the use of unique vehicle-holding coefficients for whites and blacks altered the results dramatically compared to the assumption that blacks are just like whites, only poorer. By discussing our own reservations and many of the concepts not in the MITRAM model, we have attempted to make our work more useful to those who advance or use this research.

The model to which this research has contributed, MITRAM, produces reasonable estimates for average black and white households and for a range of real gasoline prices similar to those experienced in 1981 through 1986. The use of the present (December 1988) version of the model outside these ranges will probably produce unreliable estimates that may be unrealistic in any case, since the 1981-1986 values represent the extremes for this century in real oil prices. Future recalibration of the model based on its use will undoubtedly lead to improvements.

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