7. VEHICLE MILES TRAVELED

7.1 HISTORICAL TRENDS IN ELDERLY DRIVING

The total person miles of travel for all drivers in the United States increased from 2,026 billion miles in 1983 to 2,141 billion miles in 1990 to 2,663 billion miles in 1995, a total increase of 31.4% (U.S. Department of Transportation, 1997B). Historical driving trends among the elderly also show a general increase in the annual amount of VMT per person[1] (Figure 7.1). The age group of persons over 85 have seen the largest increases. Men over 85 drove an average of 1933 miles per year in 1983, a number which more than doubled to 5166 in 1995. Women also saw a sharp increase in VMT per person in that time frame, tripling their driving miles from 1828 in 1990 to 2781 miles in 1995. Insufficient VMT data for women over 85 in 1977 and for all persons over 85 in 1983 prevented us from obtaining comparisons over a longer time frame. Increases in other elderly groups were less dramatic, but still substantial, with men between the ages of 65 and 84 increasing the number of miles driven by 35%, and women in that same age group increasing their average numbers from 35% (65-74) to 75% (75-84). This increases show changes in the driving habits of older women, who are clearly driving a substantial amount more than women of similar ages in the past. However, as shown in Figure 7.1, the rate of increase for the elderly between ages 65 and 84 was greater between 1983 and 1990 than it was between 1990 and 1995. Note that statistical changes in the 1995 VMT measures of the NPTS are believed to understate actual VMT for that time period.

Travel habits of the elderly are different from those of younger age groups. In 1995, the average person over 65 took fewer trips for every trip purpose than those under 65, with the most substantial decline, logically, in trips to earn a living (Figure 7.2). The smallest

[1] Person miles of travel includes travel by any mode or means; VMT/person implies that the person is driving the vehicle.

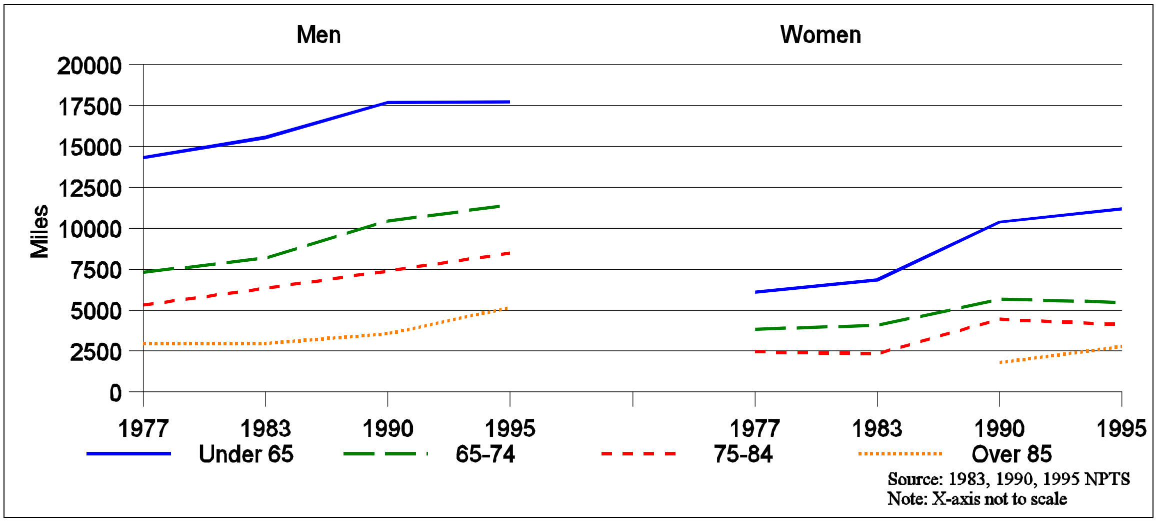

Figure 7.1. Annual Vehicle Miles of Travel per Driver, 1977-1995

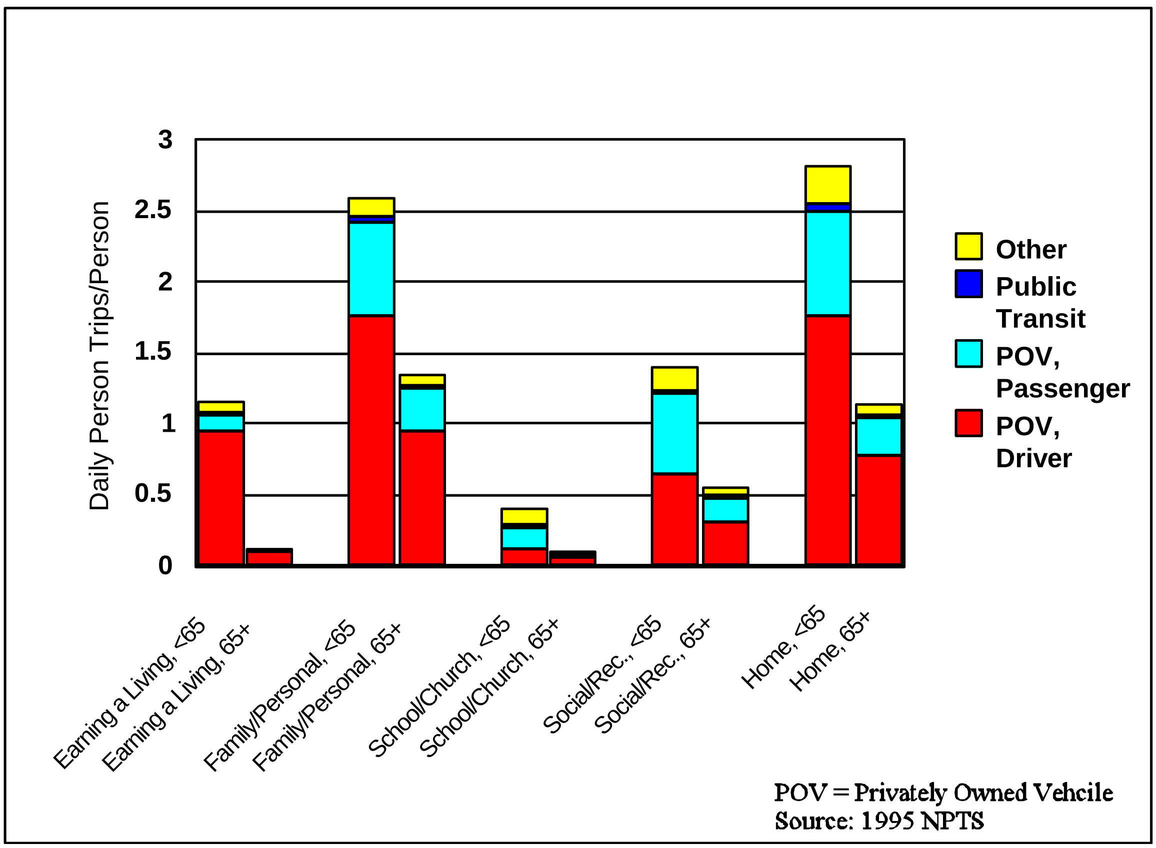

Figure 7.2. Average Person Trips per Person by Mode of Transportation and Trip Purpose, for Individuals under 65 and Individuals 65 and Over

decline in number of person trips was for the trip purpose of family and personal business. Now that we have shown how much and in what ways elderly driving has increased in the last two decades, we examine historical determinants of VMT that can be used to project VMT into the future**.**

7.2 EMPIRICAL MODELING OF VMT

We estimate the average VMT per driver using data from the 1977, 1983, 1990, and 1995 NPTS. This relationship is an economic one derived from demand theory, discussed in Section 5.2. The demand for mileage driven derives ultimately from a person's preferences, conditioned by his or her personal and external circumstances.

The demand for VMT is complicated by two factors. First, with the exception of leisure driving, VMT generally has a derived demand and is not something people would consume for its own sake. For instance, people drive to work to earn their income and they drive to the store to buy goods they want to consume, not simply for the sake of the respective trip. Thus, people's demand for VMT is derived from their demands to get to their jobs, to have the goods they purchase, to see their doctors, etc. One of the factors that creates differences in the driving patterns, and overall demands for VMT, between elderly drivers and those in the prime working ages of 25-60, is that some of the important activities from which the demand for VMT is derived are different. Particularly, the proportion of the population working declines substantially. Many of the other consumption oriented determinants of VMT demand, such as shopping trips and service-related trips, change less (US DOT, 1993, p.4-37).[2] However, having fewer hours spent working does free up the elderly, particularly the younger elderly, to consume more recreation that may demand VMT. This at least partially compensates for the reduction in work trips.

[2] Table 4.20 shows that retired individuals and couples have a far sharper decline in travel related to earning a living than for other purposes.

Second, VMT as a consumption item is something that consumers must produce themselves with combinations of their time and purchased inputs, not an item like clothing that can be purchased and consumed directly. The household production model of demand handles this aspect of the demand for VMT quite well, specifying that the consumer of VMT produces that service with a combination of time and purchased inputs (Becker, 1965, pp. 493-517). In the case of VMT, the purchased inputs are the vehicle (or at least the depreciation on the vehicle), fuel, and insurance. Both depreciation and insurance have at least theoretical relationships to VMT. Empirically, depreciation would parallel VMT more closely than would insurance payments, if for no other reason than that people have the opportunity to understate their mileage to their automobile insurance companies. Empirical observations of both depreciation and insurance costs are difficult to come by, as are observations of the amount of time drivers spend producing their VMT. The fact that time is required to produce VMT complicates the empirical interpretation of income in a demand equation of the form "VMT = f(income, prices)" because income also influences the "price" of VMT. People who earn higher incomes face a higher cost of using their time driving than do people who earn lower incomes, so the income variable in a regular demand equation contains both the ordinary income effect and a price effect. For the elderly, the price effect of income may be lessened somewhat by virtue of the fact that much of their income will come from asset sources such as retirement plans and earnings from various types of investments and savings. Consequently, their time spent driving is less likely, across all elderly in any one age group, to come out of marginal working time. Nonetheless, even with zero working time, higher incomes will cause people to value their leisure more highly, and time spent driving *will* come out of leisure.

The preferred strategy for estimating the demand for VMT would be a simultaneous equations approach jointly estimating the supply of VMT (meaning the maximum amount of VMT possible, given time constraints) and the demand for it. Data limitations, and possibly the diminished price effect of income for the elderly, precluded deriving useful results from that approach. Consequently, the regression model with which we implemented our VMT demand estimation used a specification closer to the ordinary demand equation, although we included variables to account for the derived-demand effect of working and for one substitute for driving (the availability of someone else in the household who can drive). Our basic VMT demand regression equation is:

$$\log(\text{VMT}) = \text{constant} + a_1 \log(\textit{income}) + a_2 \log(\textit{fuel price}) + a_3 \log(\textit{health status}) + a_4 (\textit{employment status}) + a_5 (\textit{other drivers available in household}) + a_6 (\textit{year}). \quad (2)$$

The logarithmic specification of the regression permits interpretation of the estimated regression coefficients as elasticities, i.e., the percent change in VMT induced by a 1% change in an independent variable. Thus the estimated value of a_2 is a *fuel price* elasticity of demand for VMT and that of a_1 is an *income* elasticity of demand for VMT. Much is known about relative magnitudes of price and income elasticities of demand, which helps in the assessment of the reasonability of the current estimates.

The *health status* variable is an NPTS representation of activity limitation status. This variable, whose construction is described in Section 5.3, is based on the ALS ranking from NHIS. This variable indicates an individual's capacity to drive, and is actually a supply-side influence used in this demand equation as a control. *Employment status* is a binary variable for in or out of the work force, and *other drivers available in household* is another binary variable indicating the presence or absence of other drivers in the elderly person's household.

The impact of the *fuel price* variable on the amount of driving was quite large (-1.5 to -2.2) relative to what is known about fuel-price elasticities (Pickerell and Simek, 1999, pp.1-17).[3] This variable caused other estimation problems, particularly in the effect of income, so the final specification omitted fuel price. The *year* variable is a measure of the changes in American society and the geography of its infrastructure over the past quarter

[3] Pickerell and Simek estimate price elasticities of VMT per vehicle (our measure is VMT per person) ranging from -0.09 to -0.34, using the 1995 NPTS and the same source for fuel price data that we use. While we can reproduce their results, the fuel price elasticities we can obtain for VMT/person do not fall below -1.5.

century on which we are unable to obtain direct, quantitative information. Some of these changes include changing family roles that have caused more women to drive; changing urban-suburban relationships that have affected shopping behavior, recreational travel, and the journey to work; and changing labor market conditions that have interacted with both of the previous changes.

In the VMT models, a separate regression was estimated for each age group, as shown in Table 7.1. The percents of variance explained by the regressions, also know as the R^2 statistic, are in a satisfactory range for regressions on large sample-size survey data, centering around a range from 0.17 to 0.29.

Let us use the men aged 65 to 69 as an example of how to interpret the coefficient results in Table 7.1. The *log(income)* coefficient of 0.3050 means that, for each 1% increase in income, VMT will increase by 0.3050%. Similarly for the *health status* variable, a 1% increase in the health status measure will cause a 0.0868% increase in VMT. Having *other drivers* in the household will lead to a decrease of 0.1279 in log(VMT), not VMT in its standard scale since the *other drivers* effect was not estimated in log-form. Being part of the workforce will lead to an increase in log(VMT) of 0.4991. Finally, for each additional *year*, the increase in log(VMT) not attributable to previously accounted for effects like *income* and *health status* is 0.0218.

Turning to overall trends in the results, the income elasticities of VMT are in the range of 0.20 to 0.46, meaning that each 1% increase in *income* will lead to an increase in VMT of 0.20% to 0.46%. This range of increase was not consistently higher across age groups for men or women. The elasticity estimate for 85+ men is 0.80 and -0.69 for 85+ women, with both being statistically significant at 5% or better. The male estimate is somewhat high to be entirely credible and the large negative estimate for the women surely is a fluke of some sort, either statistical or involving peculiarities of income in this age group of women. Section 7.3 contains an explanation of how we handle such odd estimates.

Table 7.1. VMT Regression Results

	65-69			70-74			75-79			80-84			85+		
	ß	T	Adj ß (if appl)	ß	T	Adj ß (if appl)	ß	T	Adj ß (if appl)	ß	T	Adj ß (if appl)	ß	T	Adj ß (if appl)
Men															
log (income)	0.3050	3.75		0.2542	4.32		0.3419	4.26		0.4674	3.34		0.8097	1.98	0.3818
log (health score)	0.0868	0.86	0	1.2270	3.64		0.5180	2.00		0.3366	1.35	0.4023	0.1753	0.36	
"other driver"	-0.1279	-1.79	0	-0.1061	-1.25		-0.3511	-3.33		-0.3254	-2.07		-0.8085	-2.26	-0.1800
employment status	0.4991	6.85		0.2945	2.76		0.5634	3.50		0.3870	1.14		0.5672	0.50	0
year	0.0218	3.51	0.0050	0.0394	5.16	0.0050	0.0343	3.35	0.0050	0.0314	2.24	0.0050	0.0543	1.72	0.0050
Women															
log (income)	0.2096	2.86	0.2400	0.3834	6.22	0.2000	0.1418	1.38	0.2322	0.0559	0.34	0.2000	-0.6981	-1.73	0.2000
log (health score)	0.0743	0.62	0.1751	0.3215	0.80	0.3816	0.5357	1.55	0.8129	0.5816	1.99		1.9193	2.28	
"other driver"	-0.4477	-5.60		-0.6983	-7.50	-0.4888	-0.7541	-5.58	-0.6250	-0.5765	-2.55		-0.1168	-0.25	0
employment status	0.7168	6.98		0.5933	4.39	0.4153	0.4357	1.49		0.8867	2.03	0.4500	0.7260	0.94	0.4500
year	0.0203	2.82	0.0150	0.0042	0.48	0.0150	0.0301	2.48	0.0150	0.0207	1.09	0.0150	0.0282	0.57	0.0150
R-Squared	.2122			.1747			.2339			.1890			.2962		
# of observations	2492			1746			968			430			107		

The *health status* effects are positive as expected, showing that better health status permits more driving. However, these effects are highly significant statistically for men only in the 70-74 and 75-79 age groups (marginally significant for the 80-84 group) and for women only in the 80-84 and 85+ age groups (with a marginally significant effect for the 75-79 group). It seems as if this measure of health status only has a material effect among the older women, while its effect seems restricted to men in the middle periods of old age. The magnitudes of the significant effects for both men and women are rather large, with elasticities of 1.23 and 0.52 for the men 70-74 and 75-79 and 0.58 and 1.92 for the women 80-84 and 85+.

Having *other drivers* in an elderly person's household generally has a stronger dampening effect on VMT for women than for men, but no clear pattern of effect by age emerges, suggesting that the impact of having other drivers in the household on the amount of driving does not change by age. However, that gender effect is reversed in the 85+ age group where there is no identifiable effect on women and the dampening effect on men is substantial, with its coefficient of -0.81 being larger than in any other age group.

Being in the work force generally has a stronger positive effect on women's VMT than on men's, but as with the effect of other driver, there is no clear age pattern among the magnitudes of that effect. For 75-79 year olds, the effect is stronger for men than for women. Otherwise, the effects are always larger for females than males, and the differences are statistically significant for all age groups except the 85+ group, for which both the male and female effects are not statistically significant.

The increases in VMT captured by our time trend variable, which is a proxy for other differential changes between cohort groups, are about the same for men and women among the 65-69 and 75-79 age groups. In other cases, these effects are roughly twice as large for men at any age.

7.3 PROJECTING VMT

For projection of VMT, we used our previously developed model (2) based on data from 1977, 1983, and 1990, and substituted the actual means of 1995 VMT for the constant term in the regression equation. This substitution was done in order to ensure our 2000 projections did not represent an unrealistically large departure from actual 1995 levels. We used the remaining regression coefficients to project *changes* in VMT according to projected percent changes in the values of the independent variables. The logarithms of VMT, *income* and *health status* were used in the regression, yielding regression coefficients with the forms of elasticities: the percent change in the dependent variable (VMT) per one-percent change in the independent variable (income and health status). *Employment status* and *other driver* were projected as changes in the percentages of the population in each age/gender group in the labor force (essentially a labor force participation rate for employment status) and living in a household with other drivers—changes relative to the group percentages in 1995. The regression coefficients of these variables, given the log transformation of VMT, yielded percent change in VMT caused by one-percent changes in these two variables. This projection is essentially an add-to-base method. In the absence of changes in the independent variables and exogenous growth determining annual VMT per driver, VMT would continue into the future at its 1995 rate. Only changes in those determinants of VMT, or any added time trend, will affect VMT in future years.

As explained in Section 7.2, the final VMT regressions generally were very good in terms of showing significant relationships of the expected signs of independent variables, and even explanation of the variance in VMT, considering the individual survey character of the data. Nevertheless, some of the coefficients for individual variables for specific age/gender groups showed non-significant relationships or relationships that were significant but of unusual magnitude. Rather than project VMT using these coefficients mechanically, we altered some of the coefficient values, which can be identified in the "Adjβ" column of Table 7.1. Where possible, we used information from regressions estimated under different specifications when searching for a significant coefficient value to use in place of a non-significant one in the final set of regressions. When we decided to not accept a significant coefficient value (as in the cases of the odd income effect for men and women over 85), or when no significant value was obtained in any regression, we looked for patterns of magnitudes across age groups and endeavored to use a magnitude that fit into such a pattern. Because of these substitutions, there are no consequences to any unusual coefficients found in the regressions.

Of particular importance among the altered coefficients is the exogenous growth factor (the time trend variable), which incorporates historical increases in VMT caused by factors unaccounted for in the model. Linear extrapolation of historical growth trends is a notoriously unsatisfactory projection procedure since it presumes previous behavior will continue unchanged throughout the future. Therefore, the value of the time trend coefficient was modified in the projection to be that value which would restrict the 2025 VMT for the age group consisting of 65 to 69 year-olds to the approximate levels that same group traveled as 35 to 39 year-olds in 1995. Our reasoning is that since VMT requires people to use their time, and total time available is limited, there is some upper limit to VMT as long as average travel speeds do not increase. Some ITS innovations could yield modest increases in average travel speeds, but the growth of population and natural restrictions on the increase of lane mileage can be expected to limit any such increases. In the absence of firm knowledge regarding the maximum amount of time the American population is willing to spend traveling, we take the age group with the current greatest average VMT as representing the plausible maximum time people can be expected to spend traveling in the future.[4] It could be argued that the elderly in the future (this very cohort, in fact, displaced twenty years into their future) would be unwilling to spend as much time driving as they did when they were twenty years

[4] The importance of time in the demand for VMT goes back to the household production aspect of that demand. It takes time to consume most goods. Time is a major input to VMT, and time spent traveling is a major allocation of Americans' time budgets today. It may be intuitive to think of the demand for VMT as reflecting the number of destinations for which people have a demand to reach, but when the total time spent traveling during the week reaches some number of hours—we do not have an empirical clue to what that number of hours actually is—people will begin to think twice about the "necessity" of some of their proposed, or even their traditional, destinations; they will combine some trips (trip chaining), postpone others, and possibly even drop some. While people may think in terms of destinations, their travel behavior is equally powerfully conditioned by the constraints on their time.

younger. In that case, our VMT projections can be considered as a maximum likely scenario. However, in light of all the changes in the past twenty years in characteristics of drivers, employment, technology, and infrastructure, we are unable to derive a satisfactory, purely empirical estimate of how much time the future elderly will devote to driving[5]. Hence we suggest that a healthier and wealthier elderly population driving in safer vehicles on improved highways and possibly greater distances with urban sprawl might devote as much of their time to driving as they did when they were thirty years younger, but probably not more. This maximum level of VMT allows for expected growth in the demand for VMT for specific age/gender groups while maintaining a reasonableness in the projections. While this anchors the maximum likely driving by the 65-69 age cohort in 2025, the proportional decreases in driving among older cohorts at that date depend strictly on the proportionalities in the

[5] Modeling the demand for VMT with a linear regression may inadequately capture the effects of the time it takes to travel. A person's time is, of course, limited to twenty-four hours in a day, and people typically devote blocks of time to particular types of activity: sleep, work, eating, recreation, and so on. The fact that driving takes time puts an upper limit on the amount of VMT that a person would demand, regardless of his or her income. Modeling the demand for and supply of VMT simultaneously, in a household production framework, as we suggested above would be an excellent procedure, could account for the increasing scarcity value of a person's driving time as VMT increased, imposing a cap on VMT naturally, according to the valuation a person puts on his or her time. As the valuation of the time spent driving increases as more VMT is undertaken, the cost of VMT will rise considerably, choking off the demand for it. It may be possible to develop some other methods to account for the increasing effective cost of time made available to driving which would be less demanding of data. It would not be appropriate to simply reduce the magnitudes of the income elasticities of demand for VMT estimated in our ordinary least squares regressions on the grounds that the negative effect of income on VMT, acting as the cost of driving time, is excluded, because our current specification may be allowing some part of the negative component to enter the currently estimated coefficient.

In the present research, we did not have the data to implement any form of a natural capping of the demand for VMT, hence our resort to the arbitrary capping of VMT for 65-69 year old males at the maximum VMT of any age group in 1995, which happened by circumstance to be 35-39 year olds. Picking the VMT of any other particular age group might have been preferable in some intuitive sense, but not in any empirically determinable manner; since our admittedly arbitrary method of capping the VMT projection uses only one arbitrary decision, we consider it preferable to picking a specific age group's VMT as a cap without reason to prefer that group over any other, which would involve at least two arbitrary decisions.

We are aware of one study that has addressed the demand for VMT as a household production problem, although less than fully satisfactorily. Greening et al. estimated the demand for fuel efficiency in vehicles, gasoline, and vehicle mile traveled with the seemingly unrelated regressions technique (a Generalized Least Squares technique for use in equations with correlated error terms but not with endogenous variables of one equation used as independent variables in another equation). Income appears as an independent variable in all three of their equations, but it never appears in an equation as an indicator of the cost of time spent driving. Hence there remains a specification problem in their implementation of the household production approach to estimating the demand for VMT.

empirically derived regression coefficients, and similarly with the rate of growth of VMT for each age group over the period 2000 to 2025.

The *income*, *health status*, *other driver*, and *employment status* variables, and the *year trend* were projected identically to their projections for the proportion of elderly that drives. The *year trend* variable was a simple count, beginning with 1977 = 1 and increasing by one in each subsequent year.

We present the projections of VMT in several formats. We offer a graphical presentation of aggregate national projections of VMT per capita, by age and gender, in Figure 7.3. The numbers underlying the graphs are contained in the tables of Appendix A, Tables A.1.1 through A.1.4, which present Census region as well as national projections. In a pattern of tabular presentations that will carry through each of our projections, the first pair of tables presents projections for males, the second for females. In each pair of tables by gender, the first (Tables A.1.1 and A.1.3 for VMT) presents the actual mileage projections and the second (Tables A.1.2 and A.1.4 for VMT) presents those projections as percents of 1995 actual levels.

The national average VMT for the groups of elderly men are projected to rise by 27%-51% over their 1995 levels. VMT in the 65-69 group is projected to experience the largest increase, rising from around 12,400 miles per year in 1995 to a projected 18,800 by 2025. The oldest age group of men, those 85+, experience the smallest increase, from around 5,100 miles in 1995 to 6,500 in 2025. The 2025 VMT projection drops off rather sharply as we move to the70-74 group of males, with a projected 13,700 miles in that year, while the 75-79 group is close behind with 12,700 projected miles. The drop-off is sharp again as we move to the 80-84 group, with some 8,600 projected miles in 2025. Table A.1.2 presents these mileages as percents of 1995 actual mileage.

The elderly women begin from a much smaller base of VMT in 1995, but have greater relative projected increases than men in each age group. The 65-69 women are projected to reach a national average of nearly 11,300 miles, 93% above their 1995 average. The 85+ group is projected to increase its VMT by nearly 78% over 1995 levels, to over 4,900 miles per person in 2025. The smallest increase for any age group is 70% over the 1995 level, among the 75-79 group. These increases put the women's groups' VMT by 2025 at levels approximating the VMT of the corresponding groups of men in 1995.

The regional patterns of increase are generally not uniform. That is, a percent increase higher than the national average in the VMT of one age group does not necessarily imply that VMT of all age groups in that region will grow more rapidly than the national average. Having offered that rule of thumb, however, VMT growth for all age groups of men in the West and women in the Midwest is lower than the national average, and not simply because their starting (1995) levels were all higher than the national average.[6] Projected VMT growth for the youngest group of elderly men, the 65-69 year olds, is greatest in the Midwest and least in the South, although the differences of 53% over 1995 levels in the Midwest contrasted with only 48.3% in the South are not terribly great. The oldest men's VMT is projected to grow the most in the South (32.8% over 1995 levels) and the least in the West (23.6%). Among women, the greatest projected VMT growth for 65-69 women occurs in the West (96.0% over 1995) and the lowest in the Northeast and South (88.5% and 89.6%). Among the oldest women, the 85+, the greatest growth occurs in the South (77.0%) and the lowest in the West (64.9%).

[6] Only in the South were 1995 VMT levels higher than the national average for each male age group; no region had 1995 VMT uniformly lower than the national average. Among the elderly women, no region had either higher- or lower-than-national-average VMT in 1995 in all age groups.

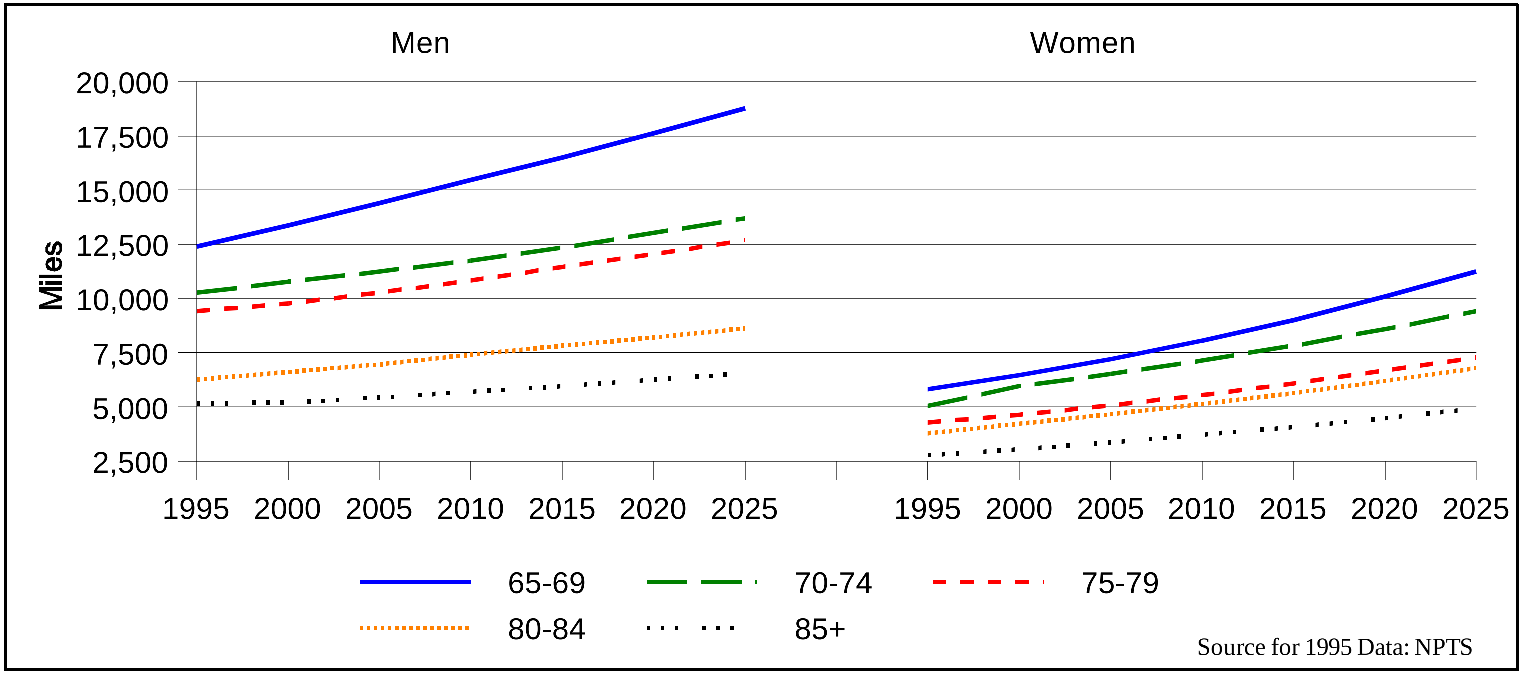

Figure 7.3. Annual Projected Vehicle Miles of Travel Per Driver

Three forces are actually operating in the projections of VMT, in the sense that their values are changing over the projection period relative to their 1995 values: income, labor force participation (LFP), and the pure time effect. The contributions of these three forces differ between men and women, among age groups, and between regions, as shown in Tables 7.2 and 7.3. These contributions reflect both the sensitivity of the driver percentage to the variable in question, as determined empirically in the regression, and the projected growth of each independent variable.[7]

Among 65-69 year old men, changes in the proportion of households participating in the labor force contributes the largest proportion of projected VMT growth. The pure effect of time, dampened as it has been between the original regressions and the projections, contributes the second-largest growth to this age group. Income contributes the least, accounting for between 22 and 27% of the increase in mileage. Among most of the older age groups, the pure effect of time contributes the most mileage growth. Income has the largest effect among 75-79 and 80-84 men in the South. In these older groups, the contribution of income growth usually exceeds the contribution of LFP growth, and the differential increases with age, as is reasonable to expect. In the oldest age groups in all regions, LFP growth has no effect because its projection coefficient was zero.

Table 7.2. Determinants of Projected National VMT Growth, 1995-2025

	Men			Women		
Age	Income	Employment status	Time	Income	Employment Status	Time
65-69	24.23%	39.62%	36.15%	13.75%	18.46%	67.42%
70-74	24.64%	20.02%	55.34%	10.07%	17.78%	72.27%
75-79	39.90%	8.76%	51.34%	10.23%	7.47%	82.23%
80-84	44.01%	9.38%	46.61%	12.66%	7.45%	79.68%
85+	42.25%	0.00%	57.75%	11.25%	7.51%	80.85%

[7] The method of assessing these contributions is to take the total differential of the VMT regression equation to obtain the expression for each variable's percent contribution to the value of the dependent variable. The differentials of the dependent and independent variables were the differences between their 2025 projected values and their 1995 actual values. The estimated regression coefficients form the basis of the coefficients on the individual contribution terms.

Table 7.3. Determinants of Projected Regional VMT Growth

	Men			Women		
Midwest						
Age	Income	Employment	Time	Income	Employment	Time
65-69	27.05%	38.18%	34.77%	13.40%	18.68%	67.91%
70-74	20.01%	21.30%	58.68%	8.02%	18.19%	73.79%
75-79	26.22%	10.79%	62.99%	6.24%	7.79%	85.97%
80-84	36.30%	10.62%	53.07%	11.98%	7.54%	80.48%
85+	44.07%	0.00%	55.93%	11.55%	7.58%	80.88%
Northeast						
Age	Income	Employment	Time			
65-69	24.11%	39.72%	36.17%	Income	Employment	Time
70-74	19.92%	21.34%	58.74%	9.61%	17.82%	72.57%
75-79	34.31%	9.63%	56.06%	10.74%	7.43%	81.83%
80-84	34.33%	10.94%	54.73%	8.93%	7.80%	83.26%
85+	41.12%	0.00%	58.88%	10.95%	7.63%	81.43%
South						
Age	Income	Employment	Time	Income	Employment	Time
65-69	22.14%	40.76%	37.10%	13.06%	18.76%	68.18%
70-74	30.30%	18.60%	51.10%	12.30%	17.23%	70.47%
75-79	46.28%	7.89%	45.83%	12.81%	7.25%	79.94%
80-84	55.26%	7.50%	37.24%	14.75%	7.30%	77.95%
85+	47.96%	0.00%	52.04%	15.29%	7.26%	77.45%
West						
Age	Income	Employment	Time	Income	Employment	Time
65-69	24.75%	39.39%	35.86%	16.92%	17.94%	65.14%
70-74	21.61%	20.88%	57.51%	7.73%	18.23%	74.03%
75-79	41.11%	8.63%	50.26%	9.41%	7.54%	83.06%
80-84	39.83%	10.04%	50.13%	13.27%	7.43%	79.29%
85+	30.45%	0.00%	69.55%	3.47%	8.26%	88.27%

The time trend accounts for the greatest proportion of VMT growth by far among women in all age groups and regions. In the 70-74 and 75-79 age groups, LFP growth contributes more to VMT growth than does income, but those relative proportions reverse in the two oldest age groups. In the 85+ age groups, other-driver growth continues to contribute to VMT growth between half and three-quarters the mileage income growth contributes with the exception of the West, where the proportions are reversed between income and LFP.

The magnitude of what we call "the pure effect of time" for want of a more precise term is striking. This effect is a combination of technological and institutional changes, and its magnitude reflects the relative contribution of this set of factors to VMT growth in the recent past. Even though we have dampened the strength of this effect from what it would have been with a linear extrapolation, its contribution is still large. One implication of this result is that if one finds our VMT projections unbelievably high, it is possible to lower them without altering the effects of either income growth or changes in elderly labor force participation, although such changes would imply particular beliefs about the progress and consequences of future technological and institutional change.