6. THE PROPORTION OF THE ELDERLY POPULATION THAT DRIVES

6.1 HISTORICAL TRENDS IN ELDERLY DRIVING

Historical data show that the percentage of the population that drives has increased over time. NPTS data from 1977, 1983, 1990, and 1995 show a general upward trend, excluding the 1995 figures, in the percent of various age groups in the population that drive (Figure 6.1). The numbers in this figure represent those persons who drive, not necessarily those who just have a license. As such, persons who call themselves drivers but did not report any mileage driven in the given survey year were not counted as drivers. This means that known problems with the statistical under-reporting of VMT in the 1995 NPTS may affect our measure of active drivers, and could account for the dip between 1990 and 1995.

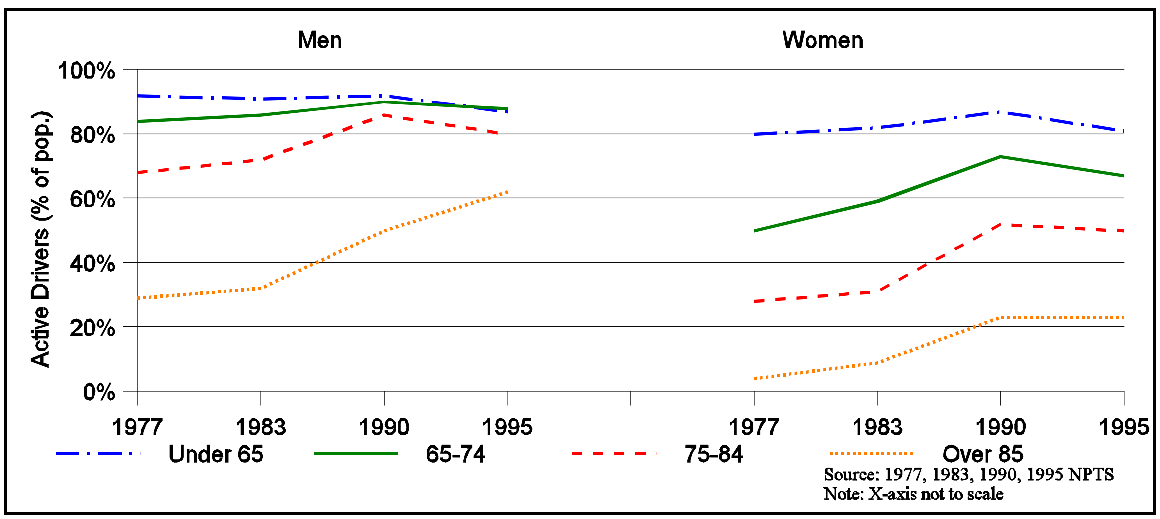

Figure 6.1. Active Drivers as a Percentage of the Population, 1977-1995

Historically, those age groups with the most room to increase have done so, with 29% of men over 85 driving in 1977, and 62% of men in the same age group driving in 1995. Similarly for women, the percentage of women over 85 who drove increased from a mere 4% in 1977 to 23% in 1995. These numbers also show the differences between men and women, which are slight in those under 65, but increase dramatically as men and women age.

Other historical data also show the decrease in the probability that a person will drive as he or she ages. A panel study that followed the same group of people for 13 years showed that as age increases, the likelihood of driving diminishes (Hu, 1995, p. 3-1 to 3-43). In the first year of the study, about 90% of women and 95% of men reported that they were active drivers. The percentages declined gradually but steadily over time, and by the thirteenth year, only 70% of women and 80% of men continued to drive.

6.2 MODELING THE DECISION TO DRIVE

The second component of our projection system involves estimation of the historical determinants of people's decisions to drive. We treat the decision to drive as an economic resource allocation decision, even if it does not involve a simple purchase in a market. This is essentially the demand framework discussed in Section 5.2.

There is no simple, empirically implementable indicator of why one continues to drive, although there are some indicators of substitutes for driving. While the proportion of Americans who are drivers has been quite high over the past several decades, income has played a clear role in determining the rate of "adoption" of driving, and income belongs in this model. We use two measures of substitutes for driving: letting someone else drive (*other driver*) and an indirect indicator of the existence of other means of getting around to one's destinations, a binary variable for an individual's residence in an urban or rural area. Ideally, access to public transportation would have been a more direct measure of the availability of alternative travel modes, but data limitations made the *urban* variable our best choice.

Employment status represents a derived demand for the decision to drive. The *year* variable captures a composite measure of the societal changes we are unable to quantify individually. *Health status* captures a person's ability to drive, as a measure with some degree of continuity, rather than his or her preference for driving.

Because the fraction of the population that can be drivers is bounded above by the value 1.0, we estimated the percentage of the elderly population that continues to drive with a logistic regression with the functional form of:

Prob (continuing to drive) = $(1+e^{-Z})^{-1}$,

where Z = constant + a_1 log (*income*) + a_2 log (*health status*) + a_3 (*urban*) + a_4 (*employment status*) + a_5 (*other driver available in household*) + a_6 (*year*).

(1)

This equation was estimated separately for age groups and by gender, with ten regressions in all.

Table 6.1 contains the results of the regressions of the model. The percent of variance in the dependent variable explained by the regressions ranges from .19 to .50, with these measures showing stronger relationships between the decision to drive and our predictors in women than in men. These adjusted R^2's, the statistics that report the percent of variance explained in each regression, are satisfactory considering the large sample sizes and the survey character of the data.

Due to the form of equation (1), our regressions, and logistic regressions in general, do not have explicitly interpretable coefficients. Note the coefficients in Table 6.1 for the men aged 65-69 as an example. The log*(income)* coefficient of 0.5829 means that for each

Table 6.1. Regression Results for the Probability of Continuing to Drive

	65-69		70-74		75-79		80-84		85+	
	ß	Prob ?^{2}	ß	Prob ?^{2}	ß	Prob ?^{2}	ß	Prob ?^{2}	ß	Prob ?^{2}
Men										
intercept	-3.7383	0.0001	-5.3709	0.0001	-3.6958	0.0001	-2.8259	0.0001	-2.3927	0.0052
log (income)	0.5829	0.0001	0.4928	0.0001	0.4150	0.0001	0.2469	0.0003	0.1838	0.0681
log (health)	0.4454	0.0001	1.5087	0.0001	0.7475	0.0001	0.6440	0.0001	-0.0069	0.9633
urban	-0.8591	0.0001	-0.4503	0.0001	-0.2979	0.0001	-0.2447	0.0010	-0.2999	0.0079
"other driver"	0.3796	0.0001	0.1985	0.0005	-0.2017	0.0017	-0.0645	0.4189	-0.5744	0.0001
employ status	0.0742	0.2366	0.6539	0.0001	0.3555	0.0019	0.6587	0.0026	0.1682	0.5429
year (MW)	0.0025	0.6205	0.0331	0.0001	0.0216	0.0002	0.0509	0.0001	0.1064	0.0001
year (NE)	-0.0283	0.0001	0.0326	0.0001	0.0304	0.0001	0.0318	0.0001	0.0642	0.0001
year (S)	-0.0015	0.7259	0.0254	0.0001	0.0213	0.0001	0.0485	0.0001	0.0498	0.0001
year (W)	0.0189	0.0012	0.0119	0.0272	0.0295	0.0001	0.0651	0.0001	0.0723	0.0001
Rescaled R-Squared	.2926		.3058		.1920		.2938		.3881	
# observations	2498		1976		1098		663		236	
Women										
intercept	-3.7481	0.0001	-6.0459	0.0001	-4.6065	0.0001	-3.6567	0.0001	-5.5528	0.0001
log (income)	0.3712	0.0001	0.4649	0.0001	0.2911	0.0001	0.2224	0.0002	0.3887	0.0001
log (health)	0.8317	0.0001	1.5064	0.0001	1.2342	0.0001	1.0860	0.0001	-0.0980	0.5695
urban	-0.4853	0.0001	-0.3577	0.0001	-0.2258	0.0001	-0.8416	0.0001	-0.4274	0.0001
"other driver"	-0.3855	0.0001	-0.5816	0.0001	-0.5810	0.0001	-1.3106	0.0001	-1.2254	0.0001
employ status	0.2307	0.0001	0.7273	0.0001	0.6524	0.0001	0.6028	0.0002	1.7372	0.0001
year (MW)	0.0433	0.0001	0.0338	0.0001	0.0574	0.0001	0.0848	0.0001	0.0809	0.0001
year (NE)	0.0010	0.0052	0.0130	0.0009	0.0192	0.0001	0.0582	0.0001	0.0493	0.0001
year (S)	0.0348	0.0001	0.0341	0.0001	0.0527	0.0001	0.0589	0.0001	0.0810	0.0001
year (W)	0.0669	0.0001	0.0355	0.0001	0.0526	0.0001	0.0870	0.0001	0.0649	0.0001
Rescaled R-Squared	.4355		.3471		.4009		.4986		.3295	
# observations	2829		2326		1484		913		468	

one unit increase in log*(income)*, the logit function, represented by Z in equation (1), increases by 0.5829. While the precise effect of log*(income)* on the probability of driving is dependent upon magnitudes of the other effects in the model, one *can* say that there is a positive relationship between income and the probability to continue driving. The 0.0001 in the “Prob ?^{2} ” column of Table 7.1, being lower than 0.05 (or 5%), indicates that a strong statistical relationship exists between income and the probability of driving.[1] Similarly, a 0.4454 coefficient for log*(health)* signifies that a one unit increase in the log*(health)* variable will lead to a 0.4454 increase in the logit function, indicating a positive relationship between the probability of driving and *health status*. The *urban* variable, as a proxy for the availability of public transportation, has a coefficient of -0.8591, logically indicating that the availability of public transit decreases the probability of continuing to drive. Since it is a dummy variable, taking on a value of 0 or 1, there is either no change to the logit model if one lives in a non-urban area, or there is a decrease of 0.8591 to the logit function if one lives in an urban area. The effect of *other drivers in the household* is also a dummy variable, where having other drivers in the household increases the logit function by 0.3796. Similarly, the *employment status* coefficient of 0.0742 means that a person who is part of the workforce increases the logit function by 0.0742. However, the "Prob $?^2$ " column shows a value of 0.2366 which, being above our standard cut-off, indicates that there may be no real relationship between being in the workforce and continuing to drive for men aged 65 to 69. The same lack of a significant statistical relationship is found in the time trends (represented by *year* in Table 6.1), which capture increases in the probability of continuing to drive not explained by income, health, etc., for the midwestern and southern regions. The time trend for the other two regions indicates that, every year, the logit function of those in the Northeast will decrease by 0.0283 and the function for those in the West will increase by 0.0189. The negative effect between time and the probability of driving in the northeast region is an anomaly, not being representative of all age groups.

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[1] The 5% figure is a standard statistical cut-off for assessing "statistical significance," which is a short-hand expression for whether the true value of an estimated statistic is likely to be different from zero. As such, these confidence levels, or significance levels, tell the probability that the true values of these regression coefficients are different from zero. Thus significance at a 5% level means that there is only a 5% chance that the true value of a coefficient is zero. A 1% confidence level is "better" than a 5% level in the sense that we can have more confidence that the true value of the coefficient is not zero. While there is no logical reason to pick any particular significance level as a cut-off, with higher percentages leading a researcher to dismiss an estimated coefficient as too imprecisely estimated to support much confidence, 5% and 1% are common levels used as separating the variables that are strongly believed to have a relationship with another variable from those that might or might not. Depending on various characteristics of the data available for a statistical study, some researchers might feel uncomfortable dismissing a variable that reaches only the 10% or even the 15% significance level. Judgment is unavoidable in using significance levels to screen variables in statistical relationships.

Now, let us look at the general effects of the variables in the model. *Income* has an extremely strong statistical relationship (significant at better than 1%) with the decision to continue driving in most age/gender groups, while males 85 or older only have a weaker, but still moderately strong statistical relationship (significant at only about 6%). Income has a tendency to influence the decision to continue driving more for a man than a woman, except in the 85+ age group where the reverse is true. The coefficients range from 0.18 to 0.58. For males, the effect of income on the decision to drive declines with age, but there is no clear age pattern among females.

A higher *health status* increases the probability to continue driving, with strong positive relationships (significant at better than 1%) for all age and gender groups except in men and women over 85, where relationships are not statistically significant. Consistent with previous research, poor health influences women not to drive more than men, except among 70-74 year olds, for whom the coefficients are the same at 1.50. For both men and women, health matters least among the 65-69 year-olds. Health status matters most in the next age group (70-74), with the magnitude declining across the 75-79 and 80-84 age groups and becoming statistically insignificant in the 85+ ages. The coefficients of this effect range from 0.44 to 1.50.

As a proxy for having public transit available, living in an urban area has a strong depressing effect on the probability of being a driver for both men and women, always with coefficients significant at better than 1%. The magnitude of this effect lessens with age for men with the exception of those over 85, and falls for women over the youngest three age groups. The effect of urbanization on a woman's probability to continue driving is largest in the 80-84 age group, but falls off among 85+ to a level nearly comparable with that of the 65-69 year-olds. Coefficients range from -0.22 to -0.84.

The presence of *other drivers in the household* has strikingly different effects for men and women. These relationships are highly statistically significant (at better than 1%) for every age/gender group except 80-84 males. Men in the 65-69 and 70-74 age groups are more likely to be drivers if there are other drivers in the household, but men in the 75-79 or 85+ age groups are less likely to drive under those circumstances. There is effectively no influence of other drivers on 80-84 year old men. Women, on the other hand, are always less likely to continue driving when there are other drivers in the household, and the strength of this effect has a general upward trend with age. Overall, the negative relationship between having other drivers and continuing to drive for women is stronger than the positive relationship for men.

Being in the labor force has a strong positive effect on the probability of women driving, with a the effect roughly increasing with age. For men the effect is always positive but is statistically significant only in the middle three age groups of 70-74, 75-79, and 80-84. Except among 80-84 year olds, being in the workforce influences a woman's decision to drive more than it does for a man. The magnitudes of the significant coefficients range from 0.23 to 0.73.

The regional time trends are generally positive (significant while negative only for 65-69 males in the northeast Census region). They also tend to be somewhat larger for women than for men and get larger for older age groups, indicating that our behavioral variables alone tend to underpredict the growth of driving among the older elderly and among women, neither of which is surprising.

6.3 PROJECTING THE PROPORTION OF OLDER POPULATIONS THAT WILL DRIVE

The percentage of each age/gender group who will continue to drive is projected with the originally estimated regression equation (1). Since values of the dependent variable are constrained (the ratio cannot exceed one), it was necessary to retain the asymptotic behavior of the dependent variable imposed by the form of the equation in the projection. For projections of future years' values of the dependent variables, the projected levels of the independent variables were substituted into the logistic equation and the new values of the dependent variables calculated.

Projecting with the constant growth rates estimated in the regressions of the probability of continuing to drive would have yielded absurd results. It is well known that projecting constant growth rates from a period in the past into an indefinite future frequently produces untenable results, and this problem was particularly prominent in the cases of these three limited dependent variables. In the projections of the proportion of elderly who will continue to drive, we used the time trend with an allowance for decreasing growth rates at every five-year interval in the future. The procedure we used is detailed in Appendix C. While this is a complicated set of adjustments to the time effect in the projections, it avoids arbitrarily changing what we consider to be the more basic coefficients relating income, employment status, presence of other drivers in the household, etc., to the driving choice. Furthermore, the basic adjustment to lower the pure time effect represented in the time trend coefficients had its own empirical basis, and the subsequent adjustments on individual coefficient values is based on a combination of how age affects the driving choice and patterns in the base projections themselves.

Aggregate projections of the independent variables were used to project the probability of continuing to drive. The projection of household income, by age, gender, and region, was supplied by DRI's projections in constant 1998 dollars, using their regional forecasting model. Those projections are reported in Tables B.5 and B.6 in the appendix, with further explanation in Appendix B.2.1. *Health status* was projected to remain at its 1995 level throughout the projection period in the base projection but was projected to grow at ¼% per year in another projection discussed in Chapter 9. The *other driver* variable was a dummy variable in the regression, taking a value zero or one for absence or presence of other drivers in the household. The value of this variable was projected for each population segment (age/gender, region) by taking the proportion of that population living in a household with other drivers (a fraction between zero and one) and maintaining that level throughout the projection period. *Employment status* was projected by extrapolating Bureau of Labor

Statistics (BLS) projections beyond 2008. For 2010-2025, we used predicted values from age/gender-specific regressions using the 1999-2008 projections versus time. The BLS data only cover age groups 65-69, 70-74, and 75+, so for each of the age groups 75-79, 80-84, and 85+, we used the 75+ projections.

The *urban* effect was projected in a manner similar to the projection of other driver and employment status. The percent of the age/gender/region sample living in urban areas in 1995, which approximated the proportions of the overall population living in urbanized areas in those regions, was projected unchanged to 2025. No authoritative projection of urbanization by region was found for the United States, and while some regions' urbanization clearly is expected to increase by 2025 (e.g., the western Census region), those of the other regions had less clear expectations. Rather than attempt either an independent projection of urbanization which was beyond the scope of the present study, or make an arbitrary set of projections which could be subject to considerable difference of opinion themselves, we retained the 1995 regional urbanization levels in the projections to 2025.

Figure 6.2 offers a graphical depiction of the projections of the proportion of elderly who will continue driving, while Tables A.2.1-A.2.4 in Appendix A report the actual numbers. Historically, the proportions of the male age groups who drive are considerably higher than the corresponding proportions in the female age groups and consequently have less scope for further growth over the twenty-five-year projection period. The percent of men in the 65-69 age group who drive is projected to rise from 84.4% in 1995 to 91.1% in 2025, an increase of 7% (not percentage *points*, but percent). The relative growth in ratios in the 70-74 and 75-79 age groups of men is about the same, but the projected increases are more substantial for the 80-84 and 85+ groups, rising from 69.1% to 82.5% (19.3%) and from 53.5% to 65.5% (22.3%) respectively. The percent of southern men 85+ driving is projected to increase by nearly 40% by 2025, almost double the national average.

In each age group, the proportion of women driving in 2025 approaches the percentage of men driving in that age group in 1995. Nonetheless, these increases represent

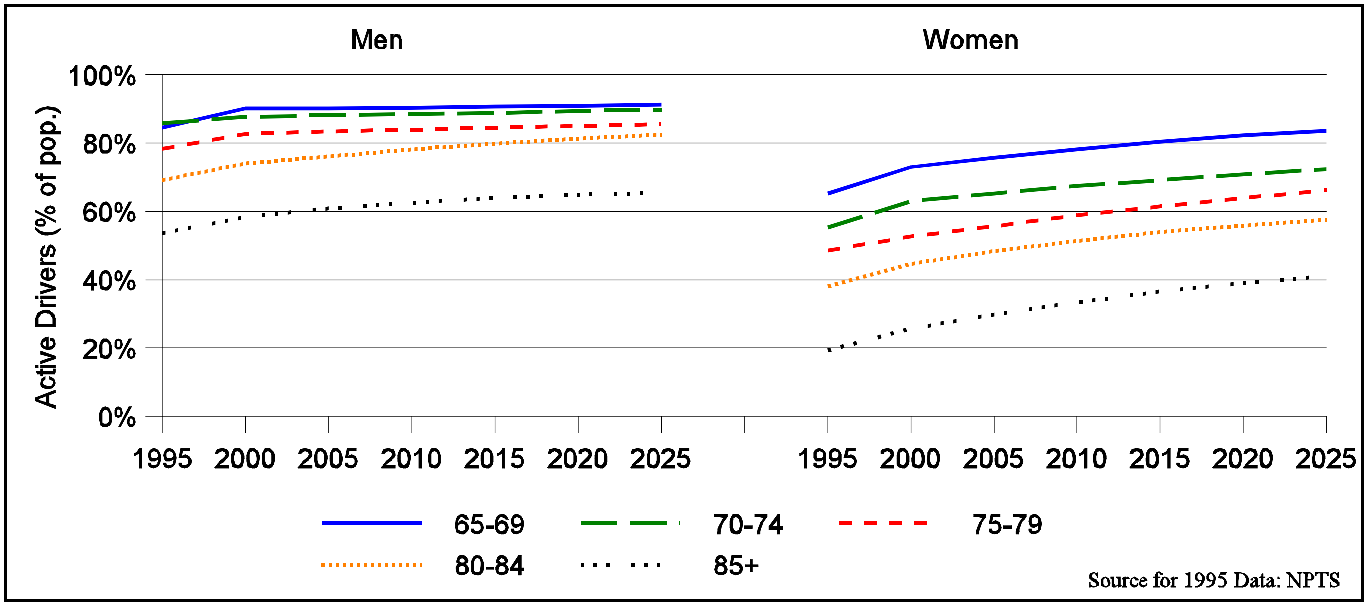

Figure 6.2. Projected Active Drivers as a Percentage of the Population

considerably greater proportional changes, with national averages in 2025 ranging from 28% higher (65-69 women) than 1995 levels to 113% (85+). The greatest proportional increases occur in the 85+ women in all regions, reaching 122% and 142% increases in the Northeast and South respectively. In 1995, 65.1% of women 65-69 were drivers nationally, with that percentage rising to 83.6% by 2025. In the West, 92.9% of women in that age group are projected to drive by 2025, but only 64.1% in the Northeast (which also had the smallest percent increase over the period). Only 19.2% of women 85+ drove in 1995, and nearly 41.1% are projected to drive by 2025, with the highest proportion in the Midwest at 52.5% and the lowest in the Northeast at 22.2%.

Tables 6.2 and 6.3 show the national and regional contributions of growth in income and labor force participation (LFP) to the projected growth in the percentage of drivers between 1995 and 2025. Income is the predominant, identifiable social determinant for men, but the influence of the time trend is dominant for women of all ages. The effect of income declines steadily by age group for men, and generally but not uniformly for women. The effect of LFP growth is minimal on women. In Table 6.3, the contribution of income growth in excess of 100% and that of LFP growth in the negative range for northeastern and southern men in the 65-69 age group reflects negative time trends in those two groups. These tables also show the enormous contribution of the pure effect of time, an indistinguishable combination of technological and institutional changes extrapolated from the past but dampened to reflect previous slowing trends. The interpretation of these magnitudes and signs is that, if it were not for the effect of the regional time trend, in both cases the driver percentage in 2025 would be substantially higher than it is with the time trend.

Table 6.2. Determinants of Projected National Driver Growth

	Men, National			Women, National		
Age	Income	Employment status	Time trend	Income	Employment status	Time trend
65-69	51.21%	2.39%	43.11%	18.08%	0.36%	82.03%
70-74	32.98%	6.90%	59.82%	20.42%	0.80%	79.35%
75-79	28.46%	0.28%	70.79%	9.76%	0.16%	90.34%
80-84	11.06%	0.35%	88.42%	6.26%	0.18%	93.53%
85+	4.83%	0.06%	95.12%	8.35%	0.04%	91.71%

Table 6.3. Determinants of Projected Regional Driver Growth

	Midwest Men			Midwest Women		
Age	Income	Employment status	Time trend	Income	Employment status	Time trend
65	81.12%	3.16%	15.72%	11.71%	0.22%	88.07%
70	28.12%	7.01%	64.88%	14.65%	0.71%	84.64%
75	13.24%	0.23%	86.52%	4.96%	0.13%	94.91%
80	5.73%	0.26%	94.01%	5.30%	0.15%	94.55%
85+	3.92%	0.04%	96.03%	6.75%	0.03%	93.22%
	Northeast Men			Northeast Women		
Age	Income	Employment status	Time trend	Income	Employment status	Time trend
65	106.71%	4.67%	-211.38%	41.43%	0.95%	57.62%
70	26.06%	7.14%	66.81%	36.69%	1.50%	61.81%
75	18.59%	0.26%	81.15%	19.65%	0.32%	80.03%
80	7.02%	0.34%	92.64%	5.98%	0.25%	93.77%
85+	3.80%	0.05%	96.15%	12.23%	0.06%	87.71%
	Southern Men			Southern Women		
Age	Income	Employment status	Time trend	Income	Employment status	Time trend
65	128.96%	6.06%	-35.02%	13.24%	0.26%	86.50%
70	46.43%	7.83%	45.74%	20.71%	0.66%	78.63%
75	43.52%	0.34%	56.14%	9.44%	0.12%	90.44%
80	20.30%	0.48%	79.22%	7.77%	0.17%	92.05%
85+	7.79%	0.08%	92.13%	9.71%	0.03%	90.26%

Table 6.3 (continued)

	Western Men			Western Women		
Age	Income	Employment status	Time trend	Income	Employment status	Time trend
65	27.70%	1.14%	71.16%	11.28%	0.17%	88.55%
70	21.68%	4.86%	73.45%	9.12%	0.48%	90.40%
75	29.98%	0.28%	69.75%	5.26%	0.10%	94.64%
80	5.78%	0.24%	93.98%	5.04%	0.13%	94.83%
85+	2.10%	0.04%	97.87%	3.35%	0.04%	96.61%