A Note on The Steady State Assumption and Expectancy Bias

Christopher C. Pflaum

George M. McCollister

Spectrum Economics, Inc.

9401 Indian Creek Parkway, Suite 360

Overland Park, KS 66210

(913) 981-7200

April 7, 2005

Abstract

The use of specialized life expectancy tables is standard practice in insurance underwriting. These tables are not, however, generally appropriate for estimating economic loss resulting from personal injury or death because the static state assumption regarding the population studied is incorrect when applied to either a cohort or individual. Because of the nature of insurance pricing, this assumption is irrelevant for that purpose. A similar bias is present in worklife tables based on a steady state assumption.

In the paper, we present the mathematical and logical problems of assuming steady state. We then show the magnitude of the bias in estimates of life and worklife expectancy that result in the case of single men.

The Steady State Assumption and Expectancy Bias

Specialized life expectancy tables that reflect sex, marital status, smoking and other factors have been used to price insurance for over a century. These and similarly derived tables have also found favor with forensic economists to estimate life and worklife expectancy in estimating economic loss due to injury or death.

These estimates can be developed from static data, examining the states of a group at a particular point in time, or by directly observing the probabilities using longitudinal data. The differences in the estimates of worklife resulting from using these methods and the strengths and weaknesses of each has been thoroughly discussed in the literature beginning with Smith (1982). However, many of dynamic variable considered in worklife and life expectancy calculations are dynamic, yet are typically treated as fixed in the development of life and worklife tables.

For example, in *Life and Worklife Expectancies*, Hugh Richards presents tables containing worklife expectancies based on several demographic classifications including age, race, gender, education, occupation, and smoking status. Richards also provides tables for female workers who have never been married and Hispanic workers based on their English language proficiency. Ciecka and Goldman (1995) estimate transition probabilities of labor force participation for smokers and non-smokers, but assume smoking status is static.

Clearly, some of these factors can be quite fluid over an individual life span. People start and stop smoking; marry, separate, divorce and marry again; and, acquire English language skills over a protracted period of residency in the United States. In each of these cases the distinguishing demographic characteristic is dynamic whereas standard tables are implicitly based on the assumption that the characteristics remain static over the individual's worklife *by constructing the tables using the proportions of persons at each age with the given characteristic who are working.*

In most cases, it is reasonable to assume that demographic characteristics will remain static over time. For example, race and gender are genetic characteristics. And, while education can continue to increase as an individual ages, it typically remains constant after the third decade of life. Conversely, there is a substantial probability that a single man will marry, an obese person will lose weight or a smoker will permanently quit.

In insurance underwriting, the assumption of a constant state for dynamic characteristics does not necessarily effect the accuracy of the estimate. For example, smokers are more likely to purchase a new life insurance policy if they quit smoking since rates are much lower for nonsmokers. This is also true for the overweight and singles. This "lapsation effect" of transitioning from a lower life expectancy to a higher life expectancy status results in the cohort remaining one of those with the life shortening attribute and the group mortality estimates being accurate.

In forensic work, however, there is no justification for assuming a constant state for the dynamic characteristics mentioned above. For example, to assume that twenty-year-old smokers will all continue to smoke for the rest of their lives would result in an estimate of life expectancy that is significantly biased. The same is true for making the same assumption for an individual in a forensic matter.

To properly capture the life and worklife effects of dynamic characteristics, an additional step is needed. First transition probabilities are needed for the characteristic. For smoking, we need the probabilities at each age of taking up the habit and of quitting. For a current smoker, we could then compute the likelihood of smoking each year in the future. These probabilities would then be applied to the corresponding labor force participation and unemployment probabilities for smokers and non-smokers to compute the probability of being alive and then summed to compute expected worklife.

Testing the Bias

Using responses to the monthly Current Population Survey (CPS), we computed the probabilities of changing marital status from one year to the next given the status for the previous year. We first identified survey responses collected between July 1999 and June 2003 that could be matched to an individual's response from the previous month. Using these observations, we computed first monthly and then annual transition probabilities by age and gender. Nearly 3.3 million responses or 69% were matched for ages 25 to 79. Table 1 displays the results for single (never married) females for selected ages. Note that between the ages of 25 and 30, over 7% marry each year.

To illustrate the difference of assuming dynamic and static marital status in calculating worklife expectancy, we compute the worklife expectancies of single male and female twenty-five-year-olds. First, we use the marriage status transition probabilities to compute the probability for each of the five marital states at each age. This is a simple Markov process. We then measure labor force participation rates by marital status. Finally we will multiply the probabilities for marital states by those for labor force participation with the corresponding martial status and sum the results to compute the probability of labor force participation at each age.

Using notation similar to Richards, let ${}^{n}N_{x}^{m}$ represent the weighted number of individuals who were in marital state m at age x and state n the previous month. The marital states are married, widowed, divorced, separated and never married. The probability of transitioning during a month from state n to state m at age x, was computed as

$$(1) \qquad {}^{n}p_{x}^{m} = {}^{\mathrm{n}}\mathrm{N}_{\mathrm{x}}^{\mathrm{m}} \,/ \sum_{m} {}^{n}N_{x}^{m}\,.$$

These probabilities are computed separately for men and woman. Given the probabilities for marital status for an individual at time t, say q_{t}^{m}, we compute the probabilities for the following month t+1 as

$$(2) \qquad q_{t+1}^{m} = \sum_{n} (q_{t}^{n}\, {}^{n}p_{x}^{m})$$

where x is the age at month t+1. If we are given the marital status for an individual at a point in time, we can thus compute the probability of being in each marital state over the remaining lifetime. Note that we have ignored mortality in these computations.

Next in our example, we compute the percent of the population that is in the labor force using the same CPS data, which for this task included nearly 5 million responses. The percent of females in the labor force by age and marital status is presented in Figure 1.

Note that prior to age 45, married woman are less likely to work than all other woman except those who are widowed. The results are the opposite for men, shown in Figure 2, where married men are much more likely to work than all other men until well after retirement.

To estimate worklife, we multiply the probabilities for marital status by those for the corresponding labor force participation status and the probability of living to that age. The expected worklife for our female subject is 29.5 years. If we assume the she never marries, however, the expected worklife is one additional year, 30.4 years. For our male subject, the expected worklife is 33.9 and 30.0 years for the dynamic and static assumptions, a difference of almost twelve percent.

Conclusion

It is perilous to assume a steady state when modeling a dynamic process yet doing so is common practice in forensic economics. This is likely because the existence and magnitude of the bias introduced is not well known and because there are no sets of tables available to forensic economists based on they dynamics of factors such as marital status and smoking behavior.

Technical Notes

Richards (1999) describes the CPS and discusses issues that arise in using this data set to compute transition probabilities for labor force participation. These probabilities depend on responses that can be matched for individuals from one year to the next. The sample frame for the CPS is residences and not individuals or families. When a residence is added to the sample, the occupants are interviewed for four months, ignored for eight months, interviewed again for four months and then removed from the sample. If the occupants move during the eight months in-between, no matches will be available for the residence. Thus,w no matches are available for a portion of the sample. Richards compared the distribution of race, education and gender for the matched sample to that for the whole sample and found small differences.

Changes in marital status, the focus of our example, will cause many individuals to move as new households are formed or old households are broken up. When matched on an annual basis, the percentage of married persons was higher than in the whole sample. We greatly reduced this discrepancy by matching responses on a monthly rather than annual time frame. Transition probabilities computed with these responses are monthly rather than annual, which only slightly increases the computation burden of computing marital state probabilities for an individual.

Richards deleted duplicate matches whereas we did not. The CPS could potentially yield up to four annual matches or six monthly matches per individual. The annual matches for an individual would mostly cover the same time period and thus contain mostly the same information. This is not true of the monthly matches in the CPS.

Ultimately, the matches need to be weighted so that transition probabilities applied to martial status in the whole sample in each month best matches that for the next period. The weights would reflect the probability of losing a match with that transition in martial status. Matches with a change in marital status would have a higher weight than those without.

Table 1

Transition Probabilities for Females Who Were Single the Previous Year						
	Age					
STATUS	20	25	30	35	40	45
Married	2.8%	7.0%	9.2%	9.3%	4.2%	3.2%
Widowed	0.0%	0.0%	0.0%	0.1%	0.0%	0.0%
Divorced	0.0%	0.1%	0.1%	0.3%	0.1%	0.2%
Separated	0.2%	0.9%	1.2%	2.3%	1.1%	1.1%
Single	97.0%	92.0%	89.5%	88.0%	94.5%	95.5%

Figure 1

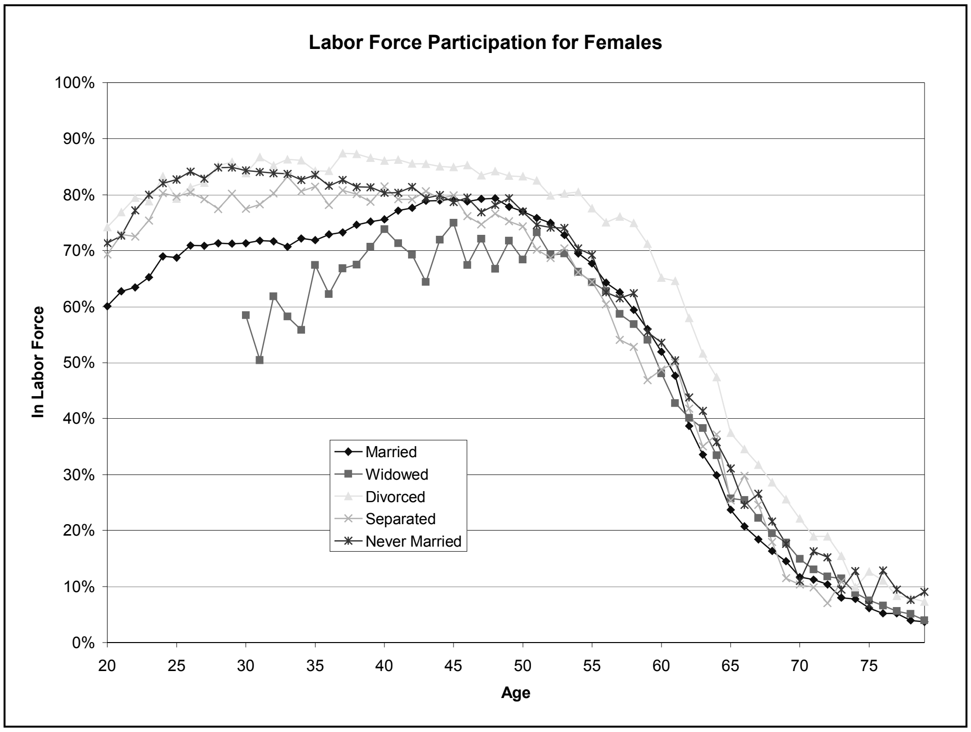
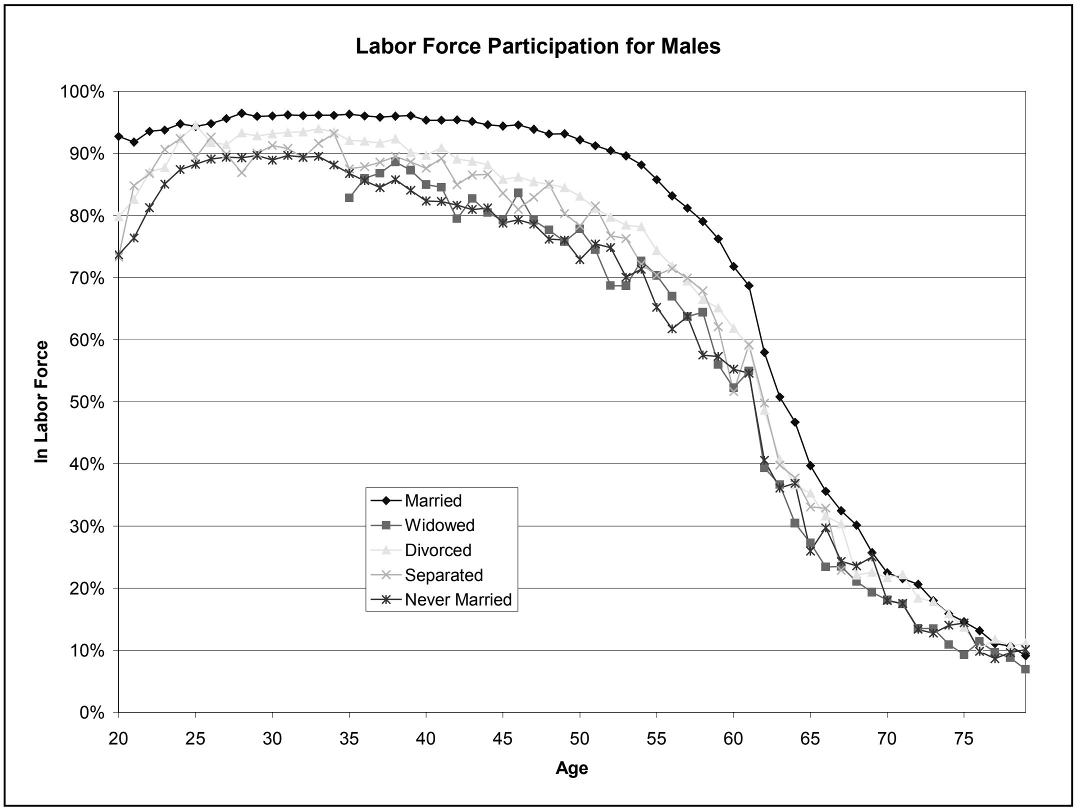

Labor Force Participation for Females
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
In Labor Force
20
25
30
35
40
45
50
55
60
65
70
75
Age
Married
Widowed
Divorced
Separated
Never Married

Figure 2



Labor Force Participation for Males
100%
90%
80%
70%
60%
50%
40%
30%
20%
10%
0%
In Labor Force
Married
Widowed
Divorced
Separated
Never Married
20
25
30
35
40
45
50
55
60
65
70
75
Age

BIBLIOGRAPHY

Ciecka, James, and Jerry Goldman. "A Markov Process Model for Worklife Expectancies of Smokers and Nonsmokers," *Journal of Forensic Economics* 8(1), 1995, 1-12.

Ciecka, James, and Thomas Donley "A Logit Model of Labor Force Participation," *Journal of Forensic Economics* 9(3), 1996, 261-82.

Ciecka, James, and Seth Epstein and Jerry Goldman. "Updated Estimates of Work-Life Expectancies Based on the Increment-Decrement Model," *Journal of Legal Economics*, 1995 5(1): 1-34.

Richards, Hugh. Life and Worklife Expectancies. Lawyers & Judges Publishing Company, Inc., Tucson, AZ. 1999.

Smith, Shirley J., *Tables of Working Life, The Increment-Decrement Model*, Bulletin 2135, US Department of Labor, Bureau of Labor Statistics, November 1982.

Smith, Shirley J., *Worklife Estimates: Effects of Race and Education*, Bulletin 2254, US Department of Labor, Bureau of Labor Statistics, February 1986.