

Estimating “The End” of Retirement

Morningstar Investment Management LLC
20 August 2020

Contents

- 1 Executive Summary
- 2 Estimating “The End” of Retirement
- 4 Life Expectancy and Mortality Rates
- 6 Estimating the Length of Retirement
- 9 The Objective and Subjective Drivers of Mortality Rates
- 16 The Importance of Personalized Mortality Assumptions in a Financial Plan
- 18 Do Financial Planners Change Mortality Assumptions for Clients?
- 21 How to Model the End of Retirement in a Financial Plan
- 26 Conclusions
- 27 References
- 28 Appendixes

David Blanchett, PhD, CFA, CFP®
Head of Retirement Research
Morningstar Investment Management LLC
david.blanchett@morningstar.com

Important Disclosure

The conduct of Morningstar’s analysts is governed by Code of Ethics/Code of Conduct Policy, Personal Security Trading Policy (or an equivalent of), and Investment Research Policy. For information regarding conflicts of interest, please visit: <http://global.morningstar.com/equitydisclosures>

Executive Summary

The length of retirement is one of the most important assumptions in a financial plan.

Retirement periods based on personalized mortality factors can vary more than 15 years, resulting in significantly different estimates for required savings and/or optimal spending levels in retirement. For example, the average person who overestimates his/her life expectancy would be expected to save 38% more than required, and the average person who underestimates his/her life expectancy would be expected to save 30% less than required.

While subjective mortality estimates are relatively accurate, on average, and appear to incorporate a number of objective aspects of mortality, there are significant errors in individual estimates. For example, individuals who said they had a 0% probability of surviving to a given age (75) actually had about a 50% chance, and those who said they had a 100% probability actually had about an 80% chance. Therefore, retirement periods should be determined using objective criteria—that is, don’t ask the client how long he/she thinks he/she will live, rather, base the estimate off objective information about the client.

Retirement end age assumptions used by financial planners in 31,211 financial plans reviewed are not that personalized, given the prevalence of certain end ages, especially those which are a multiple of five (for example, approximately 70% of plans used age 90 and 20% of plans used age 95). The assumptions used by financial advisors did also not appear to incorporate the additional “tail risk” associated with the longer potential retirement period for a married couple (that is, planning for longest survival). The length of retirement should be determined considering the shortfall aversion metric (for example, probability of success) to ensure recommendations are not overly conservative.

Adding five years to projected life expectancy for a single household and eight years to the longest life expectancy of either member of a joint household (or to each member if separate end ages are used), at retirement, is a retirement-appropriate end age assumption if the outcome variable is the probability of success (using a Monte Carlo model) and only fixed periods can be modeled (mortality rates are not directly incorporated). This approach suggests a retirement period of 30 years (to age 95) is a reasonable assumption for the average 65-year-old male/female couple retiring today.

Retirement period assumptions should be revisited regularly to ensure they are timely, similar to other key assumptions in a financial plan.

Estimating “The End” of Retirement

Introduction

The length of retirement is one of the most important assumptions in a financial plan. Despite its uncertainty, care must be taken to ensure the estimate is reasonable, because errors in forecasts can have a significant impact on estimates of how much someone must save for retirement, and how much they can spend during it.

This paper explores various factors relating to how to estimate “the end” of retirement in a financial plan. The accuracy of subjective life expectancy estimates, and the impact of objective factors, are reviewed using data from the Health and Retirement Study (or HRS) and the Survey of Consumer Finances (or SCF). While there is a robust body of literature exploring objective mortality factors (that is, the actual drivers of life expectancy), it is not clear to what extent subjective estimates are reliable and how/if objective factors are correctly considered. For example, based on data from the HRS and SCF, it appears households do a relatively good job incorporating health status into mortality forecasts, but a relatively poor job considering income and the effects of smoking. Income is a variable of considerable importance since households with higher income and more wealth are more likely to work with financial planners.¹

In theory, retirement periods should be personalized for each client in a financial plan, based on that client’s facts and circumstances, considering various attributes such as years until retirement, income, health status, smoker status, and so on. However, a review of the key assumptions in 31,211 financial plans suggests financial planners are likely not personalizing mortality assumptions, given the predominant use of certain ages and the focus on using periods in multiples of five—approximately 70% of assumed retirement end ages are age 90, and 20% of end ages are age 95.

There is no consensus approach to estimating the length of retirement among financial planners, even if the decision is based on the same underlying mortality rates (or life tables). Some planners are going to use more conservative assumptions than others, for a variety of reasons.

The projected length of retirement should be determined in conjunction with the shortfall aversion metric (for example, probability of success). Mortality is a variable that is not commonly randomized in a financial plan (for example, in a Monte Carlo setting), and assuming retirement is a fixed period and

¹ For example, based on data observed in the 2016 SCF.

estimating required savings (or available spending) based on a target probability of success can potentially result in inaccurate forecasts regarding the “success” of a given strategy.²

Through simulations it is determined that adding five years to the life expectancy estimate for a single household, and eight years to the longest life expectancy of either member of a joint household (or to each member if separate end ages are used for spouses), at the assumed retirement age, is a reasonable approach to approximating the retirement period, assuming the outcome variable is the probability of success (using a Monte Carlo model) and only fixed periods can be modeled (mortality rates are not directly incorporated). While more complex approaches that consider the distribution of mortality would be more robust, such as modeling survival stochastically, these techniques are uncommon in planning tools today. These models suggest a retirement period last lasting to age 95 (that is, 30 years) would be appropriate for the average 65-year-old male/female couple retiring today.

Like any assumption in a financial plan, mortality estimates should be regularly revisited. Mortality models, along with client health, are constantly evolving, and therefore ensuring mortality assumptions still reflect all available information is an important point to consider when updating a financial plan.

In summary, forecasting “the end” of retirement is a complex decision. There is no one single “right” way to do it; however, it is important that estimates be personalized to household attributes and that the assumed length is determined in light of other modeling assumptions, such as the probability of success, to ensure an appropriate value is selected.

Life Expectancy and Mortality Rates

Life expectancy is defined as the average number of years a person can expect to survive at a given age. For example, the life expectancy of the average newborn male, born in the United States, is 76 years³ according to the Social Security Administration 2016 Period Life Table. This means the average newborn male (age 0) would be expected to live 76 years. Life expectancy, as measured in years, tends to decline with age, but the average expected age of survival increases with age, since the person has already survived to the respective age. For example, the life expectancy of a 65-year-old male is 18 years, which implies the average 65-year-old will live to age 83, which is six years longer than a newborn.

Life expectancies are estimated using mortality tables. A mortality table includes the probability of survival for a certain population for each age. Mortality rates can vary significant across different cohorts of individuals based on different attributes or behaviors; therefore, it’s important to understand the respective population and how well it fits a given individual. For example, the Social Security Administration 2016 Period Life Table is based off the population of individuals eligible for Social Security benefits, which is effectively the entire U.S. population. Therefore, it reflects aggregate U.S. mortality rates, and would be suitable to describe life expectancies for the “average” American. It may not accurately reflect the expected mortality rates for an individual for whom more information is available (for example, whether he or she smokes).

² See Blanchett and Blanchett (2008).

³ <https://www.ssa.gov/oact/STATS/table4c6.html#ss>.

There are two general approaches for estimating life expectancy: period and cohort.⁴ Period approaches are estimated based on actual mortality experience of a given population in a certain year (that is, the probability of someone surviving during the year). For example, mortality rates in the Security Administration 2016 Period Life Table are based on the observed mortality rates for each age in the year 2016.

In contrast, cohort approaches incorporate projections into mortality rates (that is, how they may vary into the future). Cohort estimates may be largely based on observed mortality rates, but incorporate some subjective component as well (that is, a guess about how mortality rates may change in the future). Life expectancies have increased considerably over time, an effect commonly referred to as “improvement.” For example, the average life expectancy for a 65-year-old male in 1940 was 11.9 years, versus 18.1 years in 2018, and is projected to increase to 20.2 years by 2050.⁵

Ignoring mortality improvements can result in underestimating the potential length of retirement, especially for younger individuals (who are further from retirement). For example, a 1% annual improvement in mortality rates⁶ can result in a retirement period that is three years longer for someone who is retiring in 40 years (currently 25 years old), versus someone retiring today.

Client-specific factors need to be considered when estimating the retirement period given the impact of various behaviors and attributes on mortality rates (and life expectancies). Gender is one of the most well-known factors that affects mortality rates. Virtually all mortality tables have different mortality rates for males and females, where females almost always have longer life expectancies than males. For example, a newborn female, born in the U.S., has a life expectancy that is approximately five years longer than a newborn male, based on the Social Security Administration 2016 Period Life Table, and a 65-year-old has a life expectancy that is approximately 2.5 years longer.

Smoking is a behavior that has a relatively well-known negative impact on life expectancy. The Centers for Disease Control notes that mortality rates are three times higher for male and female smokers, and that life expectancy for smokers is at least 10 years shorter than for nonsmokers.⁷ Therefore, the assumed retirement period should generally be shorter for someone who smokes, versus someone who doesn’t, holding everything else constant.

Other variables, such as income, have a positive relation to life expectancy—households with higher incomes have longer life expectancies than households with lower incomes, an effect that has actually been widening. For example, Chetty et al (2016) note that 40-year-old males in the top 1% of the income

⁴ See

<https://www.ons.gov.uk/peoplepopulationandcommunity/birthsdeathsandmarriages/lifeexpectancies/methodologies/periodandcohortlifeexpectancyexplainedforadditionalinformation>.

⁵ https://www.ssa.gov/OACT/TR/2019/tr_5a4.html#proj.

⁶ Which is consistent with the long-term MP-2018 rates published by the Society of Actuaries in the fall of 2018:

<https://www.soa.org/globalassets/assets/files/resources/experience-studies/2018/mortality-improvement-scale-mp-2018.pdf>.

⁷ https://www.cdc.gov/tobacco/data_statistics/fact_sheets/health_effects/tobacco_related_mortality/index.htm.

distribution had an expected age of death of 87.3, which is 14.6 years longer than the bottom 1%. The difference had actually increased by 2.34 years from 2001 to 2014. Income is especially relevant for financial planners, since households that use financial planners tend to have significantly higher incomes.⁸

There many other factors that influence mortality, such as family history, marital status, exercise, education, location, and so on, that also warrant consideration when estimating the retirement period for a client.

⁸ Based on data observed in the 2016 Survey of Consumer Finances.

Estimating the Length of Retirement

The internet provides a wide variety of free tools, of varying levels of complexity, which an individual can use to estimate the potential length of retirement. Most tools provide a single life expectancy estimate based on the individual's current age. There are two important reasons these estimates might need to be adjusted when forecasting how long retirement might last in a financial plan.

First, the retirement period should typically be determined by assuming that the probability of surviving to retirement is 100%. While it is certainly possible that an individual may die before retiring, this outcome should not jointly be considered when assessing how long retirement may last (and how much it may cost). Therefore, mortality estimates should be based on the age (or year) of assumed retirement, not today. This is especially important for younger individuals given the impact of improvement on mortality rates over time.

Second, while life expectancy is a useful metric when estimating how long someone may survive, on average, there is approximately a 50% probability the individual will survive beyond the period. Therefore, even if the individual has a 100% probability of accomplishing their retirement goal to life expectancy, the actual probability of accomplishing the retirement is not 100% because he or she may live longer than expected. A better approach is to consider the probability of surviving to various ages and selecting some period longer than life expectancy to ensure a cushion will exist should the individual survive longer than average. Modeling periods longer than life expectancy is especially important for couples, since they typically must plan for the longer potential retirement period of either member, which introduces additional tail risk into planning.

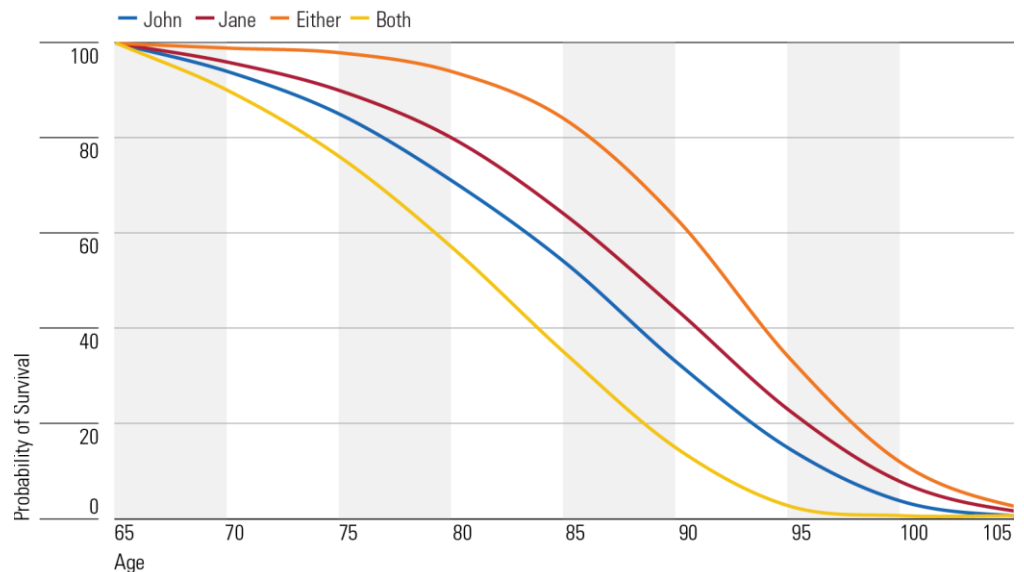
An example of an online tool, available for free, that provides insight into the probability distribution of survival for both an individual and a couple is the “Longevity Illustrator” tool made available by the American Academy of Actuaries and the Society of Actuaries.⁹ The tool incorporates attributes such as age at retirement, years to retirement (that is, improvement), gender, smoker status, and health when estimating mortality rates. The tool also determines the length of retirement, assuming the individual has a 100% probability of surviving to retirement.

The concept of survival probabilities is demonstrated in Exhibit 1, based on estimates obtained from the Longevity Illustrator tool. The analysis is based on an assumed couple, John (male) and Jane (female),

⁹ <https://www.longevityillustrator.org/>.

both age 65 in average health who are nonsmokers and currently at retirement (retiring at age 65). The probabilities of survival at various ages are included in John, Jane, either member of the couple, or both members.

Exhibit 1 Probabilities of Survival for a 65-Year-Old Couple



Source: American Academy of Actuaries and Society of Actuaries, Actuaries Longevity Illustrator.

Survival probability provides a more comprehensive perspective on the potential duration of retirement than focusing solely on life expectancy (which is just an average). For example, the median (50%) survival probability, which is generally relatively close to life expectancy, is 20 years for John, 23 years for Jane, 27 years for either member of the couple, or 16 years for both members. However, there is a 25% probability that retirement could be 26 years, 29 years, 31 years, or 22 years, for John, Jane, either, or both, respectively. Changing the probability of survival from 50% to 25% increases the potential retirement period by about six years.

Household attributes can have a significant impact on survival probabilities and corresponding retirement period estimates. This effect is demonstrated in Exhibit 2, which includes estimated retirement periods (in years) at various survival probabilities based on different health status levels (both members: poor, average, or excellent) and smoker status for the base couple (John and Jane). Again, all estimates are obtained from the Longevity Illustrator.

Exhibit 2 Retirement Periods Based on Household Types

	Probability %	Nonsmoker				Smoker			
		John	Jane	Either	Both	John	Jane	Either	Both
Poor Health	90	5	7	14	3	1	2	6	1
	75	10	13	19	7	4	6	10	3
	50	17	20	24	13	9	12	15	6
	25	23	26	28	18	14	18	20	10
	10	28	31	33	23	19	23	25	14
Average Health	90	7	9	17	4	2	4	9	1
	75	13	16	22	10	6	8	14	4
	50	20	23	27	16	12	15	19	8
	25	26	29	31	22	18	22	24	13
	10	31	34	35	26	24	28	30	18
Excellent Health	90	8	11	19	6	3	5	11	2
	75	16	18	24	12	8	10	16	5
	50	23	25	29	18	14	18	22	10
	25	29	31	33	24	21	25	28	16
	10	33	36	38	28	27	31	33	21

Source: American Academy of Actuaries and Society of Actuaries, Actuaries Longevity Illustrator.

The median (50%) survival probability period, as well as other probability estimates, change materially based on the assumed attributes. For example, if the household is assumed to be in poor health and the residents smoke, the median survival probability periods are nine, 12, 15, and 6 years for John, Jane, either or both, respectively. In contrast if the household is assumed to be in excellent health and residents don't smoke, the median survival probabilities are 23, 25, 29, and 18 years for John, Jane, either or both, respectively. There is a roughly 15-year differential in these different periods, which is relatively constant across survival probabilities.

Changing the assumed length of retirement by 15 years can materially affect required savings or recommended spending levels, and speaks to the importance of ensuring that mortality estimates are personalized to the respective household.

The Objective and Subjective Drivers of Mortality Rates

Understanding what drives mortality rates (the objective factors) and the accuracy of individual estimates (subjective estimates) is important both in determining the appropriate retirement period and having a sense of how a client will respond to the assumption. In order to understand these relations, we analyzed data from the HRS and the SCF. Both datasets have information on subjective estimates and the HRS allows us to compare the accuracy of subjective mortality estimates.

HRS Analysis

The HRS¹⁰ is a longitudinal household survey conducted by the Institute for Social Research at the University of Michigan, which surveys a representative sample of approximately 20,000 people in America, supported by the National Institute on Aging (NIA U01AG009740) and the Social Security Administration. It has been administered on a biennial basis since 1992. This analysis specifically uses data from the RAND HRS Longitudinal File, which is a user-friendly version of a subset of the HRS.

In the first wave of the HRS, administered in 1992, a question asked, “What do you think are the chances that you will live to be 75 or more?” With an average respondent age of 58, it is possible to observe the accuracy of these estimates with respect to whether the respondent actually survived to age 75.

There is already some literature exploring the accuracy of subjective mortality estimates in the HRS. For example, Hurd and McGarry (1995) note the average subjective survival probability was relatively close to the actual life table survival rates, based on the Social Security Administration 1990 Period Life Table, at 65% and 68%, respectively. Hurd (2008) compares the accuracy of the subjective estimates, and finds that they are relatively accurate on average. Most research exploring subjective survival probabilities took place before the accuracy of responses could be fully tested (that is, before most of the respondents actually turned 75).

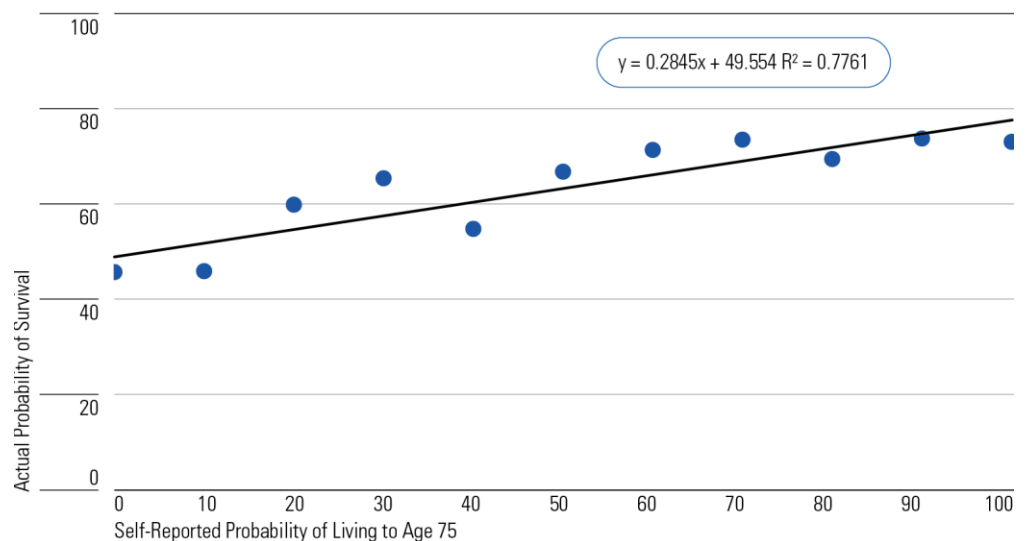
The test HRS dataset includes 3,096 respondents, which is roughly half the number of the actual respondents providing values (6,427). Additional data is required to explore how some objective criteria are related to actual mortality experience and various reasonable filters are applied, which is why the test population is notably smaller. The average self-reported probability in our dataset is 62.8%, versus

¹⁰ <https://hrs.isr.umich.edu>.

68.5% for all respondents.¹¹ As noted in past research, the average provided mortality estimate is relatively similar to the Social Security Administration 1990 Period Life Table,¹² which is the base assumed mortality table for the analysis.

Exhibit 3 includes information about the projected versus actual probabilities of survival, based on the 11 increments available to respondents, where the 0 to 10 responses are converted into probabilities, from 0% to 100%, in 10% increments.

Exhibit 3 Actual Survival Probability versus Self-Reported Probability of Living to Age 75



Source: Health and Retirement Study.

The results in Exhibit 3 suggest that there is clearly some predictive information in subjective mortality estimates, given the relatively linear relation between self-reported probability of living to age 75 and the observed (actual) mortality experience. However, there are also notable errors at both extremes. For example, among respondents who provided a 0% probability the actual survival rate was approximately 50%, and among respondents who provided a 100% probability the actual survival rate was approximately 80%.

To better understand the predictive effect of subjective mortality estimates, especially in the presence of other objective factors, a series of regressions are performed. Complete information about the regressions, and the respective results, are included in Appendix 1. All regressions include household weights.

There are a few notable results from the regressions in Appendix 1. First, many of items that appear to be related to effect subjective mortality rates (Model 1 in Exhibit A1.1) are also related to actual survival

¹¹ These values do not include weights.

¹² https://www.ssa.gov/OACT/NOTES/as116/as116_Tbl_6_1990.html#wp1085668.

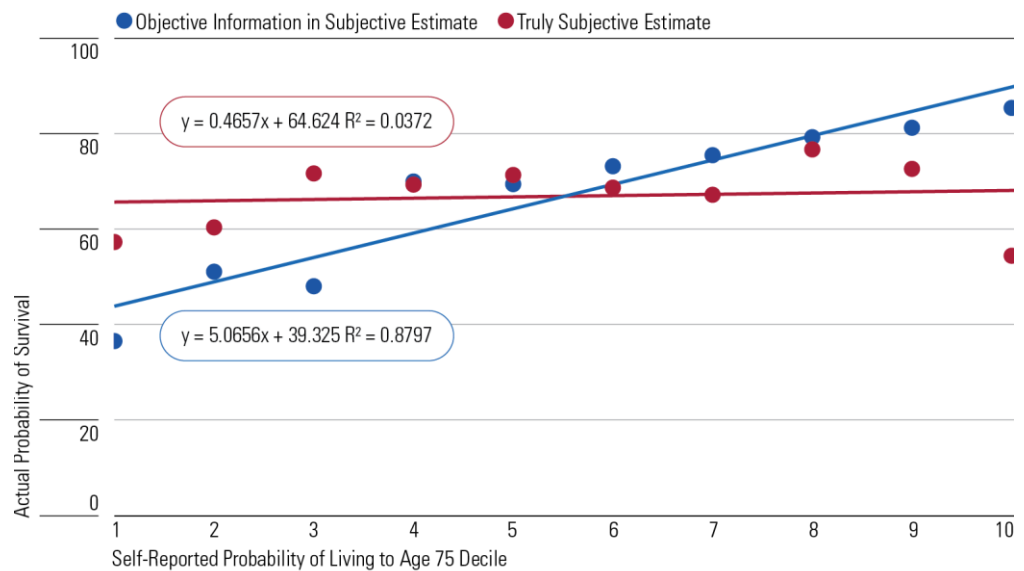
(Model 2 in Exhibit A1.1), although there are some notable differences. For example, the sign and respective size of the self-reported health status values are very similar when looking at subjective (Model 1) and objective (Model 2) differences. This suggests individuals do a relatively good job incorporating health status into survival estimates.

The relation between other variables was notably weaker. For example, whether the respondent currently smokes had a negative relation with both expected and actual survival, but the realized effect (that is, the coefficient on actual survival) was significantly greater (in absolute terms) than the subjective estimate. This suggests that smokers may realize that smoking is negatively related to survival, holding everything else constant, but may not fully understand its magnitude. Also, while the coefficient for income for the subjective regression (Model 1 in Exhibit A1.1) was not statistically significant, it was opposite of the actual effect, where there was a positive relation between income and actual survival (Model 2 in Exhibit A1.1). This relation will be revisited in the SCF analysis.

Other notable findings are that while respondents with more education expected to have higher survival rates, there was no relation when controlling for the other variables (for example, income). However, those with higher incomes did have more accurate survival estimates (Model 5 of Exhibit A1.1).

Overall, the results imply that relying on objective factors will result in far more accurate survival estimates than subjective estimates alone. It's worth attempting to disentangle the relative value of subjective estimates beyond the objective information respondents appear to be incorporating into the subjective estimates (Model 1 of Exhibit A1.1). In other words, Exhibit 3 demonstrates subjective mortality estimates are related to actual mortality; however, it's not clear whether this is just because households are correctly extrapolating objective criteria or if they do appear to have additional insights (beyond objective information) into mortality expectations.

To analyze the role of objective information in subjective probabilities, the subjective probabilities are orthogonalized with respect to the objective information using the coefficients in Model 1 of Exhibit A1.1. This results in two groups of values, which includes the objective information in the subjective estimates (that is, based on the respondent information and the coefficients from Model 1 of Exhibit A1.1) and the truly subjective information (that is, the initial estimate minus the objective values). The values for each group are placed into deciles and plotted against the actual survival rates for the group in Exhibit 4.

Exhibit 4 The Value of Subjective Estimates, Controlling for Objective Factors

Source: Health and Retirement Study.

Exhibit 4 demonstrates that once the objective information in the initial subjective estimates is controlled for, the predictive effect of the values decreases significantly. When an ordinary least squares regression is conducted (results in Exhibit A1.2), where the dependent variable is whether the respondent actually survived to age 75, and both components of the subjective estimate are considered, the objective information clearly dominates the remaining subjective component, with a coefficient that is roughly 10 times as large (note both have the same scale, which is within sample decile). These results strongly suggest that while purely subjective estimates can be used to potentially adjust forecasted retirement periods at the margins, objective information should form the primary basis of any kind of retirement period estimate for retirees.

SCF Analysis

The SCF¹³ is a triennial cross-sectional survey of U.S. families conducted by the Federal Reserve Board that includes information on families' balance sheets, pensions, income, and demographic characteristics. The study is sponsored by the Federal Reserve Board in cooperation with the Department of the Treasury. Since 1992, data have been collected by the NORC at the University of Chicago.

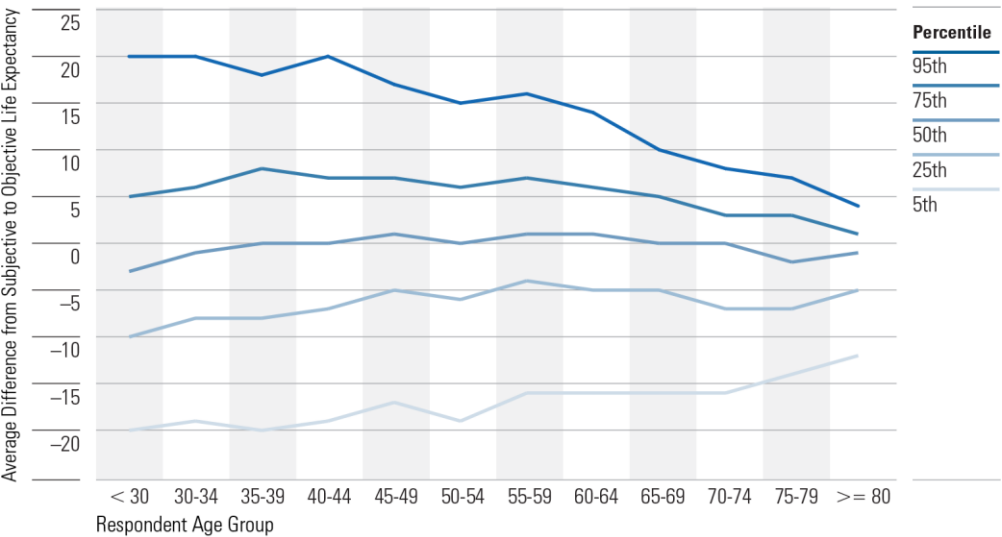
A question in the 2016 SCF asks respondents, "About how old do you think you will live to be?" This question is effectively asking the respondent to provide his or her life expectancy. Since it is not possible to directly observe the accuracy of the SCF mortality estimates, a model is created based on the

¹³ <https://www.federalreserve.gov/econres/scfindex.htm>.

observed objective mortality factors in HRS analysis that create personalized mortality estimates based on years to retirement, health, income, smoker status, and gender. The model is introduced fully in Appendix 2.

Exhibit 5 includes the distribution of errors in life expectancy estimates for the first implicate of respondents in the 2016 SCF. The error for each respondent is estimated by subtracting the objective life expectancy estimate, obtained using model created in Appendix 2, to the value provided by the respondent.

Exhibit 5 Forecasted Errors in Life Expectancy Estimates



Source: Survey of Consumer Finances.

Exhibit 5 demonstrates that while median life expectancy estimates are relatively accurate, consistent with the average self-reported probability being close to the actual expected survival probability of the HRS analysis, there are notable differences. For example, the expected error exceeded 20 years for younger respondents at the more extreme end of the distribution. Again, this suggests subjective mortality estimates should play a relatively limited role when estimating the retirement period when objective information is available.

To provide some additional perspective on factors related to respondent life expectancy estimates, and the expected errors, two regressions are performed using the SCF data. The results are included in Appendix 3. Many of the same variables used for the HRS regressions (Appendix 1) are used for the SCF regressions. The regressions include all five implicates using the repeated imputation inference method.

As a reminder, the HRS question asks about survival probability (in units from 0 to 100), while the SCF asks about life expectancy (years units) so it is difficult to directly compare the regression coefficients;

however, it is possible to compare the sign and statistical significance of the coefficients. The signs for most variables are consistent when comparing Model 1 of Exhibit A1.1 to Model 1 of Exhibit A3.1, as is the relative scale. This suggests individuals consider similar factors when generating a subjective mortality probability estimate and a subjective life expectancy estimate. When reviewing the errors in respondent forecasts, the SCF regressions suggest individuals who have more education and higher incomes have more accurate estimates, on average.

Summarizing the Objective and Subjective Impacts

In order to summarize the subjective and objective aspects of mortality, the OLS regression coefficients in Model 1 of Exhibit A1.1 and the logistic regression coefficients of Model 4 of Exhibit A1.1 are transformed into years units, versus probability, since years is a unit that is more consistent with how mortality differences are usually conveyed (and is also more intuitive). The survival probabilities are transformed by solving for the required change in mortality rates so that the estimated probability of survival equals the target value. The adjusted mortality estimates can then be used to estimate a life expectancy value (with years as the units). For example, the actual survival probability for a 58-year-old to age 75 is 68.1%. This implies a life expectancy of 22 years (to age 80). If the assumed probability of survival to age 75 is only 50% (for example, based on the respondent’s subjective estimate or the observed estimate based on attributes) the solver would estimate that multiplying actual mortality rates times 0.785 would result in a 50% estimated probability of survival to age 75 (resulting in a life expectancy of 17 years).

Mortality rates are based on the Social Security Administration 2016 Period Life Table, since it is the same year as the SCF expectations. The average respondent age in HRS data is 58, compared with 53 for the SCF data, so the values are reasonably similar. While the actual mortality experience noted in the HRS analysis (Model 5 of Exhibit A1.1) is applied to the 2016 Period Life Table, some of these values aren’t necessarily likely to persist today, since the HRS analysis is based on demographic factors as of 1992. For example, the difference in life expectancies by gender using the 1990 Period Life Table¹⁴ was four years. It had decreased to 2.5 years by 2018.

Only variables that are statistically significant at the 5% level are included. The results from the calculations are included in Exhibit 6.

¹⁴ https://www.ssa.gov/OACT/TR/2019/lr_5a4.html.

Exhibit 6 Impact of Demographic Variables on Life Expectancy (Years)

Variable	Actual HRS	Subjective HRS	Subjective SCF
Male	-4.4	-1.1	-1.2
Married	n/s	n/s	n/s
Education Years	n/s	0.2	n/s
White	n/s	-2.8	-2.3
Smoker (Ever)	-3.3	n/s	n/a
Smoker (Now)	-4.7	-0.9	-3
Income	2.2	n/s	-0.4
Health — Excellent	8	6.8	4.2
Health — Very Good	4.2	3.3	n/a
Health — Fair	-3.9	-3.9	-3.6
Health — Poor	-6.7	-6.5	-9.3

n/s = not statistically significant at 5% level, n/a = not available

Source: Health and Retirement Study and Survey of Consumer Finances.

Again, while there are notable similarities in terms of the actual noted relation between the variables and life expectancy, there are important differences. For example, it appears individuals do not fully consider the health impact of smoking on life expectancies. Additionally, while household income has a negative subjective relation to life expectancy, the actual observed relation is positive. The income relation is especially notable, because as previously mentioned, financial planners tend to work with households that have higher income levels, and because the relation between income and life expectancy has been growing.

Overall, it appears that while subjective estimates may be reasonably accurate, on average (that is, across a large group of individuals) there can be significant deviations at the individual level. This suggests financial planners should use objective criteria to estimate things like life expectancy, and may need to educate clients in situations where objective impacts differ from subjective expectations.

The Importance of Personalized Mortality Assumptions in a Financial Plan

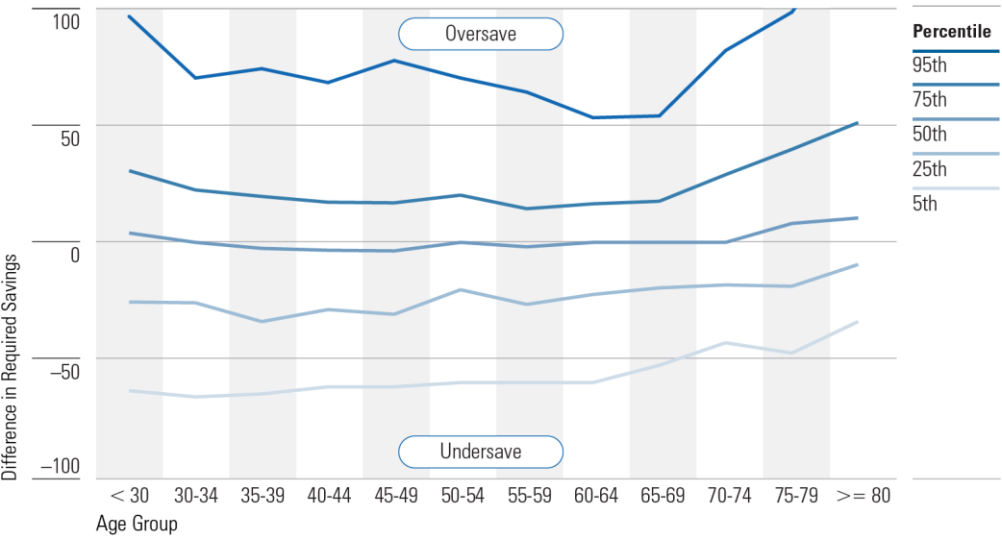
The previous analysis suggests that while mortality estimates tend to be relatively correct, on average, there is a significant deviation at the individual investor level. These can result in significantly different estimates in life expectancy, and subsequently required retirement savings. For example, based on the model introduced in Appendix 2, the life expectancy of a 65-year-old male, who makes \$25,000 a year, currently smokes, and is in poor health is 9.2 years; versus 24.8 years for a 65-year-old female who makes \$250,000 a year, has never smoked, and is in excellent health. If retirement were to be determined so that there was no more than 10% probability of outliving it, the difference in retirement periods would be 20 years (19 versus 39 years, respectively). Funding a retirement period that is projected to last 39 years is obviously significantly more expensive than one that is projected to last 19 years.

An analysis is performed to understand how retirement saving estimates could vary based on subjective and objective mortality estimates. The analysis uses the first implicate from the 2016 SCF and each respondent from the 2016 SCF is included. The analysis estimates the cost of funding retirement income, which is assumed to last from the retirement age until the respondent-provided life expectancy estimate. Retirement age is based on the age the respondent plans on accessing savings from the company-sponsored defined-contribution plan. If a value is not available and the respondent is age 65 or over, the respondent is assumed to be retired. If the respondent is under 65, the retirement age is randomly assigned with an average age of 65 and a standard deviation of 3. The value is assumed to be no less than the current age or age 55 and no greater than the current age or age 70.

The cost of retirement is determined based on the number of years from the assumed retirement age until life expectancy. Note, since the life expectancy is based on the current age, it is not consistent with how financial planners should typically estimate the retirement period. It should generally be assumed the individual will survive to retirement and then base the retirement period off that expected age (that is, assume the probability of survival to retirement is 100%); however, only life expectancies based on the respondent's current age are available, so this is the approach that must be used.

The assumed discount rate is 4% and the cost of funding \$1 of income is estimated. The retirement period is always assumed to be at least five years. Exhibit 7 includes the distribution of the differences in estimated retirement costs, at the individual participant level, using the mortality model versus the subjective estimates of the respondents.

Exhibit 7 Difference in the Cost of Retirement Using the Mortality Model versus Subjective Life Expectancy



Source: Survey of Consumer Finances.

There are significant deviations in the estimated cost of retirement using subjective estimates compared with the mortality model. For example, the average person who overestimates his/her life expectancy would be expected to save 38% more than required and the average person who underestimates his/her life expectancy would be expected to save 30% less than required.

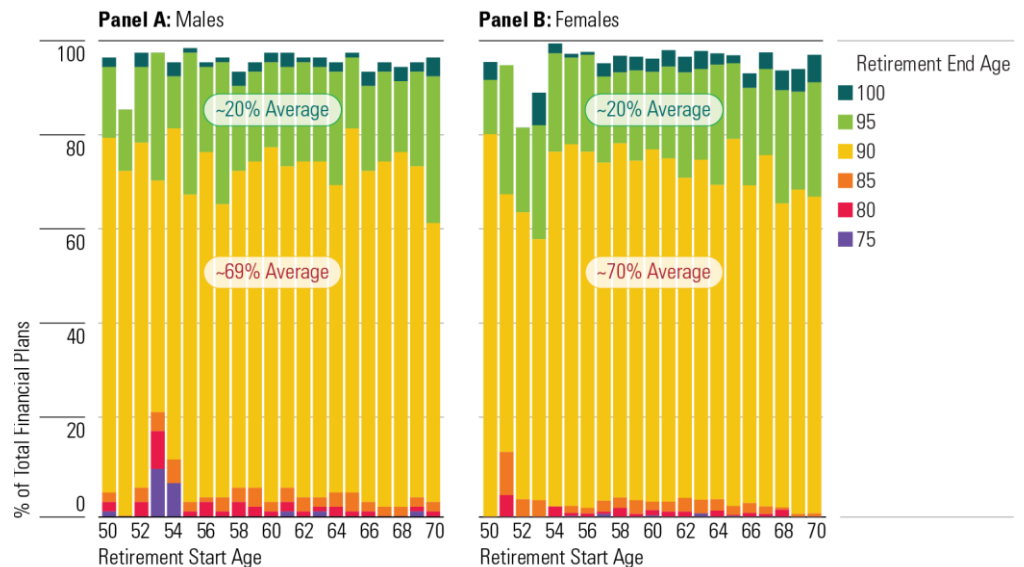
While there may be some additional information in the subjective life expectancies not captured in the objective estimates, basing retirement periods off subjective estimates can result in a significant deviation in the retirement period that would be determined using objective information. Therefore, the retirement “end age” for clients is likely best determined using objective information (for example, gender, smoking status, income, health status, and so on) and not a value provided by the client.

Do Financial Planners Change Mortality Assumptions for Clients?

The analysis so far suggests that there are factors that can significantly affect mortality rates, and that the assumed cost of retirement could vary significantly if these factors are considered. An important question, though, is to what extent financial planners consider personalized mortality factors when establishing the retirement end-date in a financial plan. To determine this, data is obtained from a financial planning platform available in Canada.

Data was filtered so that only those from the same country (Canada) are included. To be included, the plan must provide information on gender; the goal must be at least \$10,000 (in the local currency); the minimum retirement age must be 50; and the assumed length of retirement must be at least five years. Fields available include the client's age, client's assumed retirement start age, client's assumed retirement end age, and retirement goal. Age and gender fields are also available for the spouse, if provided. A total of 31,211 plans met the required filters from an initial dataset of 65,535 plans, with a total of 48,923 retirement end age estimates (the number of retirement ages exceeds the number of plans because some plans were for two people). Financial plans occurred between 2009 and 2020, with the average plan taking place in 2014.

Exhibit 8 includes the distribution of retirement end age assumptions in financial plans by gender. The vast majority (97.2%) of retirement end age assumptions were multiples of 5, between the ages 75 and 105, which is why only these multiples are included in Exhibit 8.

Exhibit 8 The Distribution of Retirement Period End Age Assumptions in Financial Plans, by Gender

Source: Anonymous Financial Planning Software.

The distribution of retirement income ages is remarkably similar by gender and age, as well as by assumed retirement start age. Approximately 70% of retirement end ages were 90, whether male or female, and approximately 20% of retirement ages were age 95. The average assumed retirement end age only increases by approximately two years for males, moving from a start age of 50 to 70 (89.8 to 91.9) versus 0.9 years for females (91.1 to 92.0).

Based on the 2013/2015 Canada Life Table,¹⁵ the life expectancy for a 65-year-old male was 19.1 years versus 22.0 for females. Therefore, a retirement end age of 90 would be approximately six years longer than life expectancy for a male and three years longer for a female. There is a 27.7% probability of a 65-year-old male surviving to age 90, versus a 40.1% probability for a female. Additionally, there is a 10.0% probability of a 65-year-old male surviving to age 95, versus a 19.0% probability for a female. Therefore, either retirement end age assumption (90 or 95) is clearly longer than life expectancy. The potential efficacy of these decisions will be discussed in a future section, especially as it relates to married couples.

An OLS regression is performed to better understand the variables related to retirement end age estimates. The dependent variable was the retirement end age, and independent variables included client age, client retirement age, client retirement goal, client gender, and whether the client was married. The results of the regression are included in Appendix 4.

¹⁵ https://www150.statcan.gc.ca/n1/pub/84-537-x/2019002/xls/2013-2015_Tbl-eng.xlsx. This represents the average of the respective financial plan date.

The regression results are interesting in a few respects. First, it appears male life expectancy retirement end age values are only 0.6 years less than females, on average. Also, life expectancy estimates are lower for those who are married. While the ultimate length of retirement is going to be based on whichever spouse is assumed to live longest, retiree households with two members face more tail risk, since the assets must fund a period so long as either is alive. Therefore, some additional margin should generally be assumed for a married couple versus a single retiree.

There is a notable effect by retirement income goal, where a client with an income goal exceeding \$75,000 would have a retirement period that was roughly two years longer than someone with an income goal of \$25,000, holding everything else constant. Additionally, retirement end ages appear to increase by age and when retirement is assumed to commence, consistent with how life expectancies evolve over a lifetime.

It is not clear how representative the information reviewed is of all financial plans (that is, it is not necessarily as representative of the decisions of financial planners like the SCF and HRS are of U.S. households). However, the strong pull towards certain numbers (for example, age 90 and 95, as well as using ages that are a multiple of five) suggests that that majority of retirement end ages are likely not all that personalized to each client. Why financial advisors are not personalizing mortality estimates, and the approaches used to forecast end ages, definitely warrants additional research.

How to Model the End of Retirement in a Financial Plan

Households that use financial planners report higher average health, a lower probability of smoking, and higher income levels based on data in the 2016 SCF. Each of these attributes suggests that households who use financial planners are likely to have a longer retirement than the “average” American household. This is why Krueger (2011) suggests using the Society of Actuaries immediate annuity table, versus tables such as the Social Security Administration’s Period Life Table, when estimating survival probabilities in a financial plan. The 2012 Individual Annuity Mortality Table¹⁶ is the most recently released version (versus the 2000 version cited in the paper).

Even once suitable mortality rates have been determined, there is no consensus approach to estimate the length of retirement in a financial plan. In other words, planners using the exact same mortality table could reach very different conclusions about what a suitable length of retirement is for planning purposes. In this section we explore how to determine a suitable value.

When determining the retirement period, it’s important to consider the shortfall aversion metric used as part of the financial plan. Financial planners are increasingly relying on Monte Carlo projections, where the probability of success is the outcomes measure—that is, required savings or optimal spending are determined based on a target probability of success. While the probability of success is imperfect because it fails to capture the magnitude of failure, it allows for the introduction of uncertainty in financial plans and is therefore a more robust assessment of a given strategy than a pure deterministic forecast.

The only random variable in financial plans that incorporate Monte Carlo forecasts is typically returns (that is, returns are the only stochastic variable) and retirement is generally assumed to last a fixed period (for example, 30 years). In theory, mortality could be randomized as well, since first estimating a conservative retirement period (for example, one where there is only a 20% probability of outliving) and then overlaying a conservative shortfall target (for example, targeting a 90% success rate) can result in a level of required savings that is considerably higher than the true failure metric (that is, the probability of being broke while alive). Therefore, it’s important to consider the shortfall aversion metric when determining the retirement period to ensure the financial plan does not result in overly conservative estimates for required saving (or spending).

¹⁶ <http://www.naic.org/store/free/MDL-821.pdf>.

In theory, the length of retirement should be determined based on personalized mortality rates, and the target success rate (or shortfall aversion metric) should be related to the client's risk aversion associated with accomplishing a goal. From this perspective two clients with identical health situations retiring at the same age would have the same retirement period, but could have very different target success rates based on their desired comfort around maintaining a certain standard of living during retirement. For example, the retirement period for both clients would be 30 years, but the client who is more risk-averse might have a target probability of success of 90%, versus 75% for the one who is more risk-tolerant.

Note: Basing the retirement period off personalized mortality estimates and using the probability of success as the risk-aversion measure does not mean the retirement period should subsequently be based off life expectancy (that is, a roughly 50% survival probability). There are interaction effects at play when it comes to selecting the length of retirement, and it should generally be a period longer than life expectancy. This section explores how to estimate the appropriate period.

First, a series of Monte Carlo projections are performed. For the projections, the portfolio is assumed to be 40% equities and 60% fixed income, where the risk level remains constant through retirement. Equities have an assumed annual return of 8% and a standard deviation of 20%. Fixed income has an annual return of 4% and a standard deviation of 7%. The correlation between equity and fixed income is assumed to be 0.1 and there is an annual assumed 1% fee assessed to the portfolio. Inflation is assumed to be 2%. Returns are assumed to follow a normal distribution.

The households considered are male, female, and joint, where the joint household is composed of a male and a female the same age. All individuals are assumed to be age 65 and at retirement. Mortality rates are based on the Society of Actuaries Individual Annuity Mortality (2012 IAM) Table with improvement to the year 2020. Using these mortality rates, life expectancy for a 65-year-old male is approximately 22 years, and 24 years for a 65-year-old female. The analysis considered 10,000 Monte Carlo runs.

The analysis estimates safe initial withdrawal rates, where the initial withdrawal amount is assumed to increase annually with inflation. This is consistent with the approach taken by Bengen (1994). While there is research that suggests retiree spending does not increase annually with inflation (for example, Blanchett 2014), assuming an annual increase with inflation is the most common assumption in financial plans today.

Exhibit 9 includes the results of various projections. Panel A includes the initial safe withdrawal rates for various target probabilities of success and retirement periods. This is included primarily for reference purposes. Panel B includes the initial safe withdrawal rates where "failure" is defined as the household being alive (either member if joint) and the portfolio not being able to sustain the withdrawal amount. This is estimated by multiplying the respective success probabilities by the probability of the household dying in the respective year. This approach captures the true success rate of the respective strategy because a retiree household only truly "fails" if he/she/they are still alive when the assets have been depleted. Panel C includes how long the assumed retirement period would last based on based on

various target survival probabilities (that is, the probability of not outliving the retirement period) and includes life expectancies for John and Jane. The maximum joint period is based on the maximum value for either member of the respective couple or the actual survival probability distribution for the couple.

Exhibit 9 Projection Assumptions and Safe Initial Withdrawal Rates

Panel A: Initial Withdrawal Determined Using Fixed Periods

Target Success Rate %	Retirement Period (Years)						
	20	25	30	35	40	45	50
95	3.80%	2.90%	2.50%	2.10%	1.90%	1.70%	1.60%
90	4.70%	3.60%	3.00%	2.60%	2.30%	2.00%	1.80%
80	5.40%	4.40%	3.70%	3.20%	2.80%	2.60%	2.30%
75	5.40%	4.60%	3.90%	3.40%	3.10%	2.80%	2.60%
60	5.40%	4.70%	4.20%	3.80%	3.50%	3.30%	3.10%
50	5.80%	4.80%	4.30%	3.90%	3.60%	3.40%	3.20%

Panel B: Initial Withdrawal Determined Based on True Failure and Corresponding Fixed Period Year

Target Success Rate %	Male		Female		Joint	
	w%	Period	w%	Period	w%	Period
95	3.10%	25	2.90%	26	2.60%	28
90	3.60%	26	3.40%	27	3.20%	28
80	3.90%	28	3.70%	30	3.50%	32
75	4.10%	28	3.90%	30	3.60%	33
60	5.00%	23	4.70%	25	4.20%	30
50	5.40%	22	5.10%	24	4.60%	27

Panel C: Length of Retirement (Years) Period Based on Survival Probability

	Single		Joint	
	Male	Female	Max Sing.	Actual
Life Expectancy	22	24	24	n/a
Survival Probability %				
50%	26	28	28	31
40%	26	28	28	31
30%	28	30	30	32
20%	30	32	32	34
10%	33	35	35	36
5%	35	37	37	38

Source: Author's calculations.

Optimal initial withdrawal rates vary considerably based on the target retirement period and that target success rate (Panel A). Not surprisingly, optimal initial withdrawal rates that incorporate mortality rates also vary based on the assume retiree household type (Panel B). Independently selecting a retirement period and a success rate can lead to a significantly different initial withdrawal rate than considering them jointly. For example, the 20% survival probability period for the couple is 34 years (Panel C). If a financial planner were to select the closest retirement period with a five-year increment (35 years), and select a relatively conservative success rate, such as 90%, the resulting initial withdrawal rate would be

2.6%. In reality, a 2.6% initial withdrawal rate has a 95% probability of success when incorporating mortality rates. If the couple actually wanted to target a 90% success rate, their actual initial withdrawal rate should be 3.2%, which is 23.1% higher ($3.2\%/2.6\% = 1.231$).

In theory, considering the distribution of survival rates is probably the best way to consider personalized mortality rates; however, these calculations can be complex, especially for a joint household (that is, estimating the probability of either member surviving to a given period). These survival rates are also not always available in online tools, which tend to focus on life expectancy. Therefore, a model is developed that keys off life expectancy and determines the additional number of years that should be added to life expectancy to result in a reasonable retirement period.

The analysis uses the first implicate from each household from the 2016 SCF to create a dataset of 6,248 potential retiree households. The assumed retirement need is based on the household type (joint or single) and assumes the retirement age for each individual is the age noted that funds would be withdrawn from retirement savings. If a value is not available it is randomly seeded, assuming a mean of 65 with a standard deviation of three years. If it is a couple household, the spouse is assumed to retire at the same time, but there could be an age difference in spouses, which is assumed to be no greater than 20 years.

For each household the probability of survival for each year is estimated using the mortality model outlined in Appendix 2.

For each household the number of years that would need to be added to the life expectancy value to result in the actual target success rate (which considers mortality) is estimated. Median survival mortality is used for joint couples. Success rates of 95%, 90%, 80%, and 75% are targeted since they represent the general range of success rates used by planners.

The results are included in Exhibit 10 for single households (Panel A), for joint households using the longer life expectancy of either couple (Panel B), and the median survival probability for the joint couple (Panel C).

Exhibit 10 Distribution of Retirement Period Adjustments by Target Probability of Success

Target Probability of Success												
Percentile	Single Household				Joint Household (Max of Single LEs)				Joint Household (50% Joint Probability)			
	95%	90%	80%	75%	95%	90%	80%	75%	95%	90%	80%	75%
5th	5	5	3	1	6	6	6	4	2	2	2	1
25th	5	5	5	3	7	7	7	6	3	3	3	2
50th	5	6	5	3	8	8	8	7	3	3	3	2
75th	6	6	5	4	8	8	8	7	4	4	3	2
95th	7	7	6	4	15	11	9	8	10	6	4	3

Source: Author's calculations.

The results in Exhibit 10 suggest that for a single household, adding five years to a personalized life expectancy estimate would be a way to estimate an appropriate retirement period (Panel A). For joint households, eight years should be added to the longest life expectancy of the two members (Panel B), or three years if the retirement period considers the actual joint survival probabilities (Panel C).

The difference in the estimated add-on for joint households compared (Panel B) with single households (Panel A), which is approximately eight years versus five years, respectively, reflects the tail risks associated with joint households. Again, this suggests retirement end age estimates need to be longer for joint households. This is the opposite of the effect noted in financial plans reviewed, where end age estimates were lower for couples versus single households (see the regression results in Appendix 4).

The life expectancy for a 65-year-old female based on the Social Security Administration 2016 Period Life Table is 20.5 years, versus 23.9 years for the Society of Actuaries Individual Annuity Mortality (2012 IAM) Table with improvement to the year 2020. This suggests 30 years is likely a reasonable approximate assumed retirement period for the average 65-year-old couple (male and female) today, using the previously noted 8-plus years approach to estimating the retirement period. However, the optimal period will obviously vary significantly based on the attributes of the respective household.

Conclusions

Personalized mortality estimates can have a considerable impact on the results of a financial plan. The assumed retirement period not only affects things like required savings and optimal spending, but also important decisions such as when someone can retire, and how much he or she needs to save. Additionally, decisions about how to fund retirement—whether to delay claiming Social Security retirement benefits, to purchase an annuity, and others—are going to be affected; therefore, it is important to ensure the estimate is as accurate as possible.

This paper explores various considerations associated with how to estimate the appropriate retirement end age in a financial plan. Evidence suggests that while subjective estimates may be relatively accurate, on average, and that households appear to do a relatively good job considering various objective factors (for example, health status) there are often significant errors in individual forecasts and households do not appear to correctly consider all the relevant objective factors (such as income). Therefore, financial planners need to educate themselves on how to better model and personalize mortality assumptions into financial plans.

A review of financial planning assumptions suggests that retirement age assumptions are likely not that personalized given the significant use of certain retirement end ages (for example, 90 and 95) and the focus on numbers with a multiple of 5. Additionally, while the assumptions used appear reasonable for a single retiree, care should be taken when considering the length of retirement for a couple given the tail risk associated with either member surviving significantly longer than average.

Similar to return estimates and other key assumptions in a financial plan, the retirement end age assumptions should be regularly reviewed to ensure they are timely and reflect all available information about both the client and mortality tables. ■■■

References

American Academy of Actuaries and Society of Actuaries, Actuaries Longevity Illustrator, <https://www.longevityillustrator.org/> (accessed April 16, 2020).

Bengen, William. 1994. "Determining Withdrawal Rates Using Historical Data." *Journal of Financial Planning*, vol. 7 no. 4: 171-180.

Blanchett, David. 2014. "Exploring the Retirement Consumption Puzzle." *Journal of Financial Planning*, vol. 27, no. 5: 34.

Blanchett, David and Brian Blanchett. 2008. "Joint Life Expectancy and the Retirement Distribution Period." *Journal of Financial Planning*, vol. 21, no. 12: 54-60.

Chetty, Raj, Michael Stepner, Sarah Abraham, Shelby Lin, Benjamin Scuderi, Nicholas Turner, Augustin Bergeron, and David Cutler. 2016. "The Association Between Income and Life Expectancy in the United States, 2001-2014." *Journal of the American Medical Association*, vol. 315, no. 16: 1750-1766.

Hurd, Michael. 2009. "Subjective Probabilities in Household Surveys." *Annual Review of Economics*, vol. 1: 543-562.

Hurd, Michael and Kathleen McGarry. 1995. "Evaluation of the Subjective Probabilities of Survival in the Health and Retirement Study." *Journal of Human Resources*: S268-S292.

Krueger, Cheryl. 2011. "Mortality Assumptions: Are Planners Getting it Right?" *Journal of Financial Planning*, vol. 23, no. 12: 36-37.

Milevsky, Moshe and Chris Robinson. 2000. Self-Annuitization and Ruin in Retirement." *North American Actuarial Journal*, vol 4, no. 4: 112-129.

Appendixes

Appendix 1: HRS Regressions

Variables included in the analysis are detailed below:

- ▶ Respondent age
- ▶ Respondent Gender: Coded as 1 if male, else 0
- ▶ Respondent Race: Coded as 1 if the respondent identifies as White/Caucasian, else 0
- ▶ Respondent Married: Coded as 1 if the respondent identifies as being a couple, else 0
- ▶ Respondent number of years of education
- ▶ Total household income: This includes all sources of income, the natural logarithm of income is used in the regression
- ▶ Whether respondent currently smokes: Coded as 1 if currently smokes, else 0
- ▶ Whether respondent has ever smoked: Coded as 1 if respondent has ever smoked, else 0
- ▶ Respondent self-reported health status: The health levels for the HRS are Excellent, Very Good, Good, Fair, and Poor. This is a categorical variable and therefore each status is included as dummy variable. A health status of “Good” is assumed to be average and is the omitted variable.
- ▶ Respondent self-reported probability of surviving to age 75: Responses for only those in the first wave (survey year 1992) are included.
- ▶ Whether respondent actually survived to age 75: Data on death age is provided in subsequent HRS waves; therefore, whether or not the respondent actually survived to age 75 is known.

The five regressions are:

- ▶ **Model 1:** OLS Regression using the HRS data. Dependent variable is the self-reported probability of surviving to age 75, which ranges from 100 to 0. Independent variables include age, gender, race, whether married, years of education, household income, whether ever smoked, whether currently smokes, and self-reported health status. The goal of this regression is to understand which factors are related to subjective mortality estimates.
- ▶ **Model 2:** OLS Regression using the HRS data. Dependent variable is the whether the respondent actually survived to age 75 (equals 100 if survived, else 0). Independent variable is the self-reported probability of surviving to age 75. The goal of this regression is to understand whether the subjective probability is related to actual survival, ignoring the other objective factors. While the dependent

variable is binary, and therefore approaches like a logistic regression are likely more appropriate, this is included to more easily compare subjective and objective mortality estimates.

- ▶ **Model 3:** Logistic Regression using the HRS data. Dependent variable is the whether the respondent actually survived to age 75 (equals 1 if survived, else 0). Independent variable is the self-reported probability of surviving to age 75. The goal of this regression is to understand whether the subjective probability is related to actual survival, ignoring the other objective factors.
- ▶ **Model 4:** Logistic Regression using the HRS data. Dependent variable is the whether the respondent actually survived to age 75. Independent variables include age, gender, race, whether married, years of education, household income, whether ever smoked, whether currently smokes, and self-reported health status. The goal of this regression is to understand which factors are actually related to mortality (that is, objective factors) as well if the subjective probability coefficient is still significant.
- ▶ **Model 5:** Logistic Regression using the HRS data. Dependent variable is the absolute error in the predicted probability of surviving to age 75 and whether or not the respondent actually survived. Independent variables include age, gender, race, whether married, years of education, household income, whether ever smoked, whether currently smokes, and self-reported health status. The goal of this regression is to understand which attributes are associated with better mortality estimates.

The results of the regressions are included in Exhibit A1.1

Exhibit A1.1 HRS Regression Results

Model#	1	2	3	4	5
Dataset	HRS	HRS	HRS	HRS	HRS
Regression Type	OLS	OLS	Logit	Logit	OLS
Dependent Variable	Survival Probability	Whether Survived	Whether Survived	Whether Survived	Survival Error
Intercept	45.533**	66.314**	0.042	0.669	67.688***
Age	0.429	-0.159	—	-0.01	0.042
Male	-3.226**	-11.572***	—	-0.620***	5.423***
Couple	1.256	2.286	—	0.129	-2.261
Education Years	0.507**	-0.005	—	-0.001	-0.189
White/Non-Hispanic	-9.024***	1.247	—	0.095	-1.154
Smoker/Ever	-0.798	-7.141***	—	-0.443***	0.401
Smoker/Now?	-2.735*	-14.615***	—	-0.682***	2.477
Income	-0.489	2.208***	—	0.115***	-0.849*
Health — Excellent	14.901***	12.532***	—	0.705***	-8.076***
Health — Very Good	8.022***	7.946***	—	0.403***	-3.673*
Health — Fair	-13.171***	-12.931***	—	-0.532***	-1.597
Health — Poor	-24.919***	-27.311***	—	-1.136***	-5.124*
Survive Probability	—	—	0.011***	0.003*	-0.257***
Observations	3,095	3,095	3,095	3,095	3,095
R ²	18.31%	15.12%	n/a	n/a	10.01%

*** significant at .1% level, ** significant at 1% level, * significant at 5% level

Source: Health and Retirement Study.

A second OLS is performed where the dependent variable was whether the individual actually survived to age 75; if so it is coded as 100, else 0. The two independent variables are based on the provided subjective probability, which is decomposed into objective and (truly) subjective factors using Model 1 of Exhibit A1.1. The results are included in Exhibit A1.2.

Exhibit A1.2 Decomposing Subjective Probabilities Into Objective and Subjective Factors

Model#	Coeff	SE	t	Pr > t
Intercept	37.47	2.298	16.305	0.000
Objective Probability	5.071	0.278	18.211	0.000
Subjective Probability	0.551	0.28	1.967	0.049
Observations	3,095			
R ²	9.82%			
Adjusted R ²	9.76%			

Source: Health and Retirement Study.

Appendix 2: Mortality Model

A model is created to generate personalized mortality rates based on the unique attributes of an individual. The model is based on both the observed predictors of mortality using the HRS regressions (Exhibit A1.1) as well as other research on what affects mortality rates

The model uses the Social Security Administration’s 2016 Period Life Table¹⁷ as the basis for mortality calculations. Mortality rates are modeled using the “Gompertz Law of Mortality,” named for Benjamin Gompertz. Gompertz discovered that a person’s probability of dying increases at a relatively constant exponential rate as age increases. The specific formulation of Gompertz’s law for mortality is based on Milevsky and Robinson (2000), where the probability of survival to age t , conditional on a life at age (a), is given by equation A2.1.

$$q_t = \exp \left\{ \exp \left\{ \frac{a-m}{b} \right\} \left(1 - \exp \left\{ \frac{t-a}{b} \right\} \right) \right\} \quad [A2.1]$$

where m is the modal lifespan and b is the dispersion coefficient. Gompertz’s parameters are estimated by fitting the actual mortality rates to the modal lifespan and dispersion coefficient values that minimize the sum of squared differences from our parameters and the base mortality estimates, which is the average probability of survival by age for a male and female, both age 65. The modal lifespan and dispersion coefficients are estimated to be 86.97 and 9.68 years, respectively.

If the model is used to estimate probabilities of survival for a couple, the mortality rates are assumed to be independent. If mortality rates are estimated based on a future retirement date, the assumed probability of survival until retirement is 100%.

¹⁷ <https://www.ssa.gov/oact/STATS/table4c6.html>.

The modal value is adjusted based on unique household information. Adjustment factors include gender, health status, smoker status, and income level, and incorporate future expected improvements in mortality. The respective adjustments are summarized below.

An Excel version of model has been created and is available at: www.davidmblanchett.com.

Gender

The modal adjustment for females is 1.25 years versus negative 1.25 years for males. This is consistent with the observed difference in life expectancy at age 65 in Social Security Administration’s 2016 Period Life Table, which is 2.5 years. The differences in life expectancies at age 65 have decreased from four years in 1990 to 2.5 years today.¹⁸ If gender is not known for an individual, for some reason, there would be no modal adjustment.

Health

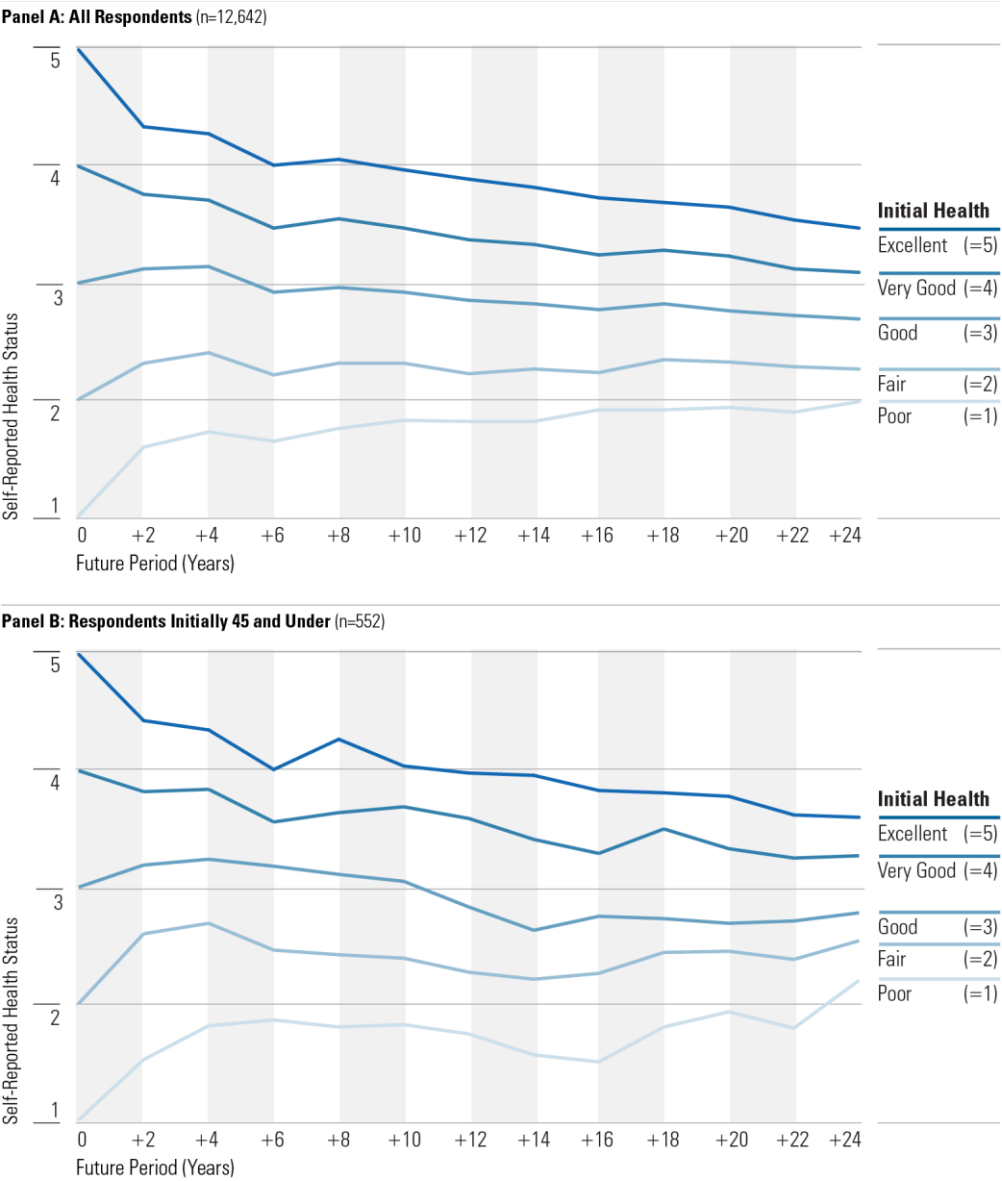
The impact of self-reported health is relatively monotonic (R^2 of 98.12% for a linear regression) across the five self-reported health status levels in the HRS, which are Excellent, Very Good, Good, Fair, and Poor, based on the HRS regressions in Exhibit A1.1. Therefore, the modal value is assumed to change by 2.5 years for each level/response away from a self-reported health status of “Good,” which is assumed to be average health. This adjustment is roughly consistent with the respective impact on life expectancy in the logistic regression.

For mortality calculations based on current age the current health status is used. For calculations based on some future age (for example, retirement) the health status is adjusted to reflect the potential change in health status into the future (it may get better or worse over time).

The adjustments are based on how the self-reported health status evolves for participants in the initial HRS wave, conducted in 1992. Exhibit A2.2 includes the initial self-reported health values, and how the scores for the five respective levels (Poor, Fair, Good, Very Good, and Excellent) evolved over the period. Note: The actual scores are the reverse of what’s coded in the HRS (where 1 is Excellent and 5 is Poor) so that a higher self-reported health value equates to better health.

¹⁸ https://www.ssa.gov/OACT/TR/2019/lr_5a4.html.

Exhibit A2.2 The Evolution of Self-Reported Health Status



Source: Health and Retirement Study.

Note, health-reported health scores tend to converge towards the average over time. For example, 20 years after the initial HRS wave, respondents who described themselves in Excellent health (score = 5) had an average health score of 3.65, which is roughly halfway between Good (= 3) and Very Good (= 4). While average self-reported health scores declined for those in Excellent health, they improved for those respondents who initially described themselves in Poor health. This suggests self-reported health status should be adjusted if the mortality calculations begin at some point in the future (for example, if the

individual is currently 45 years old and retiring at 65 years) to reflect the uncertainty of how health status may evolve over time.

The relations noted in Exhibit A2.2 are approximated using equation A2.2, where the future self-reported health status ($Health_F$) is a function of self-reported health status ($Health_0$) and the years until the mortality rates are calculated (YtC), which would generally be retirement.

$$Health_F = 1.5 + Health_0(.65 - .009(YtC)) \quad [A2.2]$$

The respective future self-reported health status estimate is then converted to a modal adjustment ($Health_{LE_Adj}$) using equation A2.3.

$$Health_{LE_Adj} = 2.5(Health_F) - 7.5 \quad [A2.3]$$

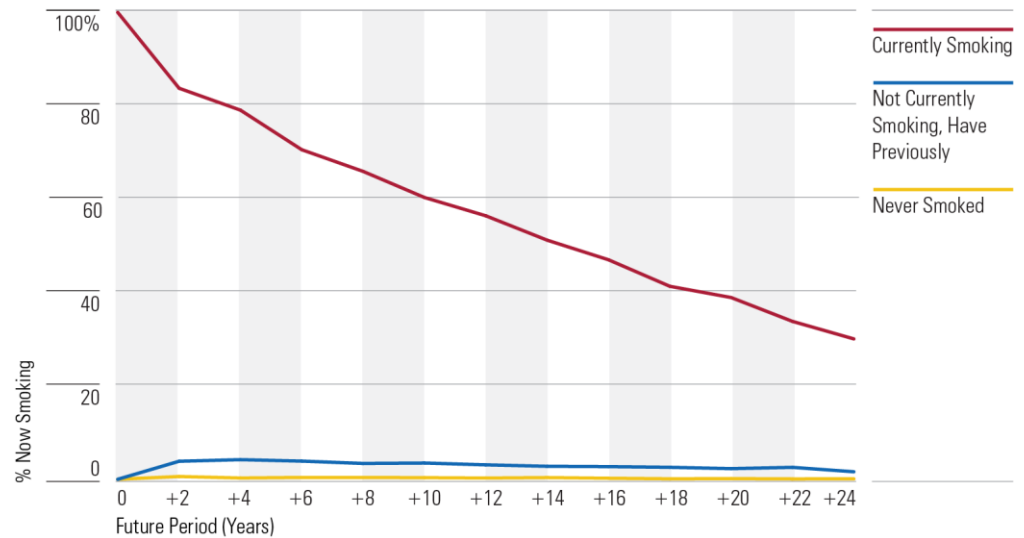
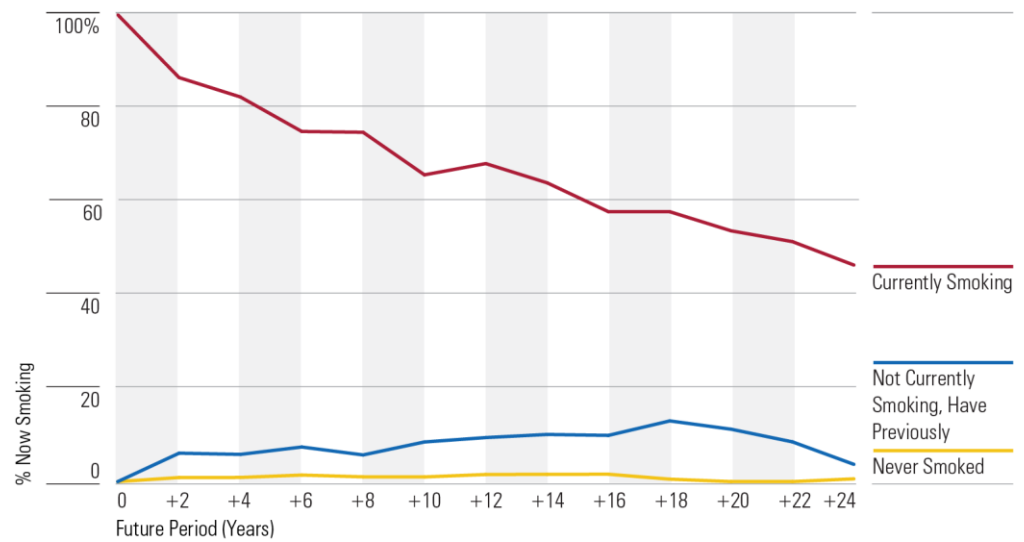
The health status is only adjusted from its current value if mortality rates are assumed to begin at some point in the future. If mortality rates are based on current age, then current self-reported health status is assumed.

Smoking Status

Smoking has a significant, negative impact on life expectancy.¹⁹ Therefore, considering whether an individual smokes is an important component to estimating mortality rates. The mortality adjustments for an individual based on his/her current age if he/she is currently smoking are relatively straightforward (and are assumed to be reduced by six years); however, just because someone is not currently smoking does not mean he/she has never smoked, and just because someone is smoking now does not mean he/she will be smoking at some point in the future (that is, at retirement, especially the further retirement is in the future).

To determine how smoking status evolves over time, data from the HRS is reviewed, based on responses to the initial wave (1992). The percentage of respondents who classify themselves as currently smoking is broken out in three groups: those who are currently smoking (who, by definition, will have previously smoked); those who are not smoking currently but have smoked previously; and those who have never smoked. How the smoking status for these respective groups evolves over the period for all respondents and those respondents under 45 and under is included in Exhibit A2.3, respectively.

¹⁹ https://www.cdc.gov/tobacco/data_statistics/fact_sheets/health_effects/tobacco_related_mortality/index.htm.

Exhibit A2.3 The Evolution of Smoking Status**Panel A: All** (n=12,642)**Panel B: Respondents Initially 45 and Under** (n=552)

Source: Health and Retirement Study.

In terms of the distribution by the three groups: 27% of all respondents and 32% of respondents age 45 and under are currently smoking; 36% of all respondents and 22% of respondents age 45 and under are not currently smoking, but have previously; and 37% of all respondents and 46% of respondents age 45 and under have never smoked. It appears relatively safe to assume someone who is not currently smoking does not start smoking, nor has he or she smoked previously (since the odds of becoming a smoker appear to be relatively low).

The probability that someone who is currently smoking, then stops smoking, increases over time. The probability of people currently smoking declines to 39% for all respondents 20 years into the future (an annual decline of approximately 3%) and to 54% for respondents initial age 45 and under (an annual decline of approximately 2.5%). These reductions are similar to research by the CDC (2017), which notes approximately 55% of smokers made attempts to stop smoking in the previous year (ranging from 66.7% for those age 18-24 to 47.2% for those age 65-plus), and of those approximately 7% were successfully able to do so (ranging from 9.9% for those age 18-24 and 5.4% for those age 65-plus).²⁰

For the Analysis

Someone who is not currently smoking is assumed to have not smoked in the past nor will be smoking in the future, so there is no modal change. For someone who is currently smoking, a modal reduction of three years is assumed regardless of the years until the base calculation age (that is, retirement), since this person will have smoked, regardless if he or she stops smoking.

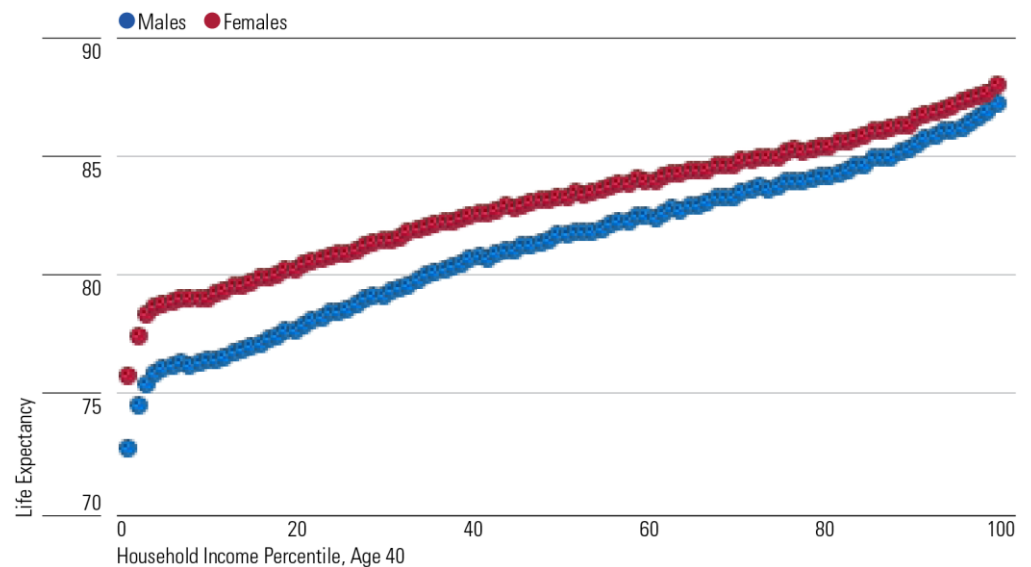
The modal reduction associated with currently smoking is assumed to be four years; however, the reduction is assumed to reduce by 3% per year until the calculation (that is, retirement) year, reflecting the average probability of the individual quitting by year. Therefore, if the mortality calculations commence in more than 33 years, the individual will be assumed to not currently be smoking. For example, a projection for a smoker based on his or her current age would result in a modal reduction of seven years ($3+4 = 7$). The modal reduction for a projection for someone who currently smokes but whose mortality rates are assumed to commence in 20 years (that is, the individual is currently 45 years old and retiring at age 65, in 20 years) would be 5.6 years ($3+(4*(1-(20*.3))) = 5.6$).

Income

Household income is becoming increasingly related to mortality/life expectancy. For example, from 2001 to 2014 life expectancy for men (women) in the top income quartile, with an average income of \$256,000 (\$243,000), increased by 0.20 (0.23) years per year; life expectancy for those in the bottom income quartile, with an average income of \$17,000 (\$16,000), only increased by 0.08 (0.10) years per year. This has led to a growing divide in life expectancies by income level, as noted in Exhibit A2.4, for 40-year-old males and females based on data from the Health Inequality Project²¹ published by Chetty et al (2016), with a range of 14.6 years for males and 12.3 years for females.

²⁰ <https://truthinitiative.org/research-resources/quitting-smoking-vaping/what-you-need-know-quit-smoking>.

²¹ <https://healthinequality.org/>.

Exhibit A2.4 Life Expectancy by Income Percentile for a 40-Year-Old

Source: Chetty et al (2016).

The analysis uses current total household income to determine the modal impact of income. This is obviously a simplifying assumption because wages tend to change over the life cycle, and as such so too would relative income levels (that is, which percentile an individual falls in). However, the rate of change associated with income over the life cycle varies by attributes such as gender and education, as well as when the individual enters the workforce. The base wage (that is, no modal change) is set to \$60,000, which is consistent with the same approximate income level noted in the HRS survival probability analysis (1992 wages converted to 2016 dollars) and the analysis in Exhibit A1.4, where the individual is assumed to be 40 years old and mean wages are \$57,237 and \$57,005 for females and males at the 50th percentile, respectively.

The impact of wages on the modal value is assumed to be nonlinear to reflect required income growth to move into higher income percentiles, where the natural logarithm of wages is used in the calculation, as noted in equation A2.4.

$$Income_{LE_Adj} = 2(\ln(Income_0) - 22) \quad [A2.4]$$

The maximum potential modal adjustment is assumed to be two years (positive or negative). This is obviously less than the effect noted in Exhibit A1.4. That's because other factors that are related to income are controlled for individually in the model. For example, households with higher incomes are less likely to be smokers and are more likely to have higher self-reported health levels (as noted in the previous regression analysis using the HRS data). Additionally, the impact of income on life expectancies

declines with age (as life expectancies decline), to a range of 5.1 years for females and 8.2 years for males by age 65.

Mortality Improvements

Life expectancies have increased considerably over the past few decades and are generally expected to continue increasing into the future.²² Decreasing mortality rates (that is, increased life expectancies) is an effect commonly referred to as “improvement.” For the model, mortality improvements are based on the long-term MP-2018 rates (for years greater than or equal to 2034) published by the Society of Actuaries in the fall of 2018.²³ These are 1% from ages zero to age 85, and then decline linearly to zero to age 115.

Appendix 3: SCF Regressions

Variables included in the analysis are detailed below:

- ▶ Respondent age
- ▶ Respondent Gender: Coded as 1 if male, else 0
- ▶ Respondent Race: Coded as 1 if the respondent identifies as White/Caucasian, else 0
- ▶ Respondent Married: Coded as 1 if the respondent identifies as being a couple, else 0
- ▶ Respondent number of years of education
- ▶ Total household income: This includes all sources of income. The natural logarithm of income is used in the regression.
- ▶ Whether respondent currently smokes: Coded as 1 if currently smokes, else 0
- ▶ Respondent number of years of education
- ▶ Total household income: This includes all sources of income. The natural logarithm of income is used in the regression.
- ▶ Whether respondent currently smokes: Coded as 1 if currently smokes, else 0
- ▶ Self-reported health status: the health levels are Excellent, Good, Fair, and Poor (there is no “Very Good” status for the HRS). This is a categorical variable and therefore each status is included as dummy variable. A health status of “Good” is assumed to be average and is the omitted variable.
- ▶ Subjective life expectancy: The actual question for respondents is, “About how old do you think you will live to be?” The responses are continuous and bounded between the ages of 20 and 150.

²² https://www.ssa.gov/OACT/NOTES/pdf_studies/study120.pdf.

²³ <https://www.soa.org/globalassets/assets/files/resources/experience-studies/2018/mortality-improvement-scale-mp-2018.pdf>.

The two regressions are:

- **Model 1:** OLS Regression using the SCF data. Dependent variable is the self-reported life expectancy. Independent variables include age, gender, race, whether married, years of education, household income, whether currently smokes, and self-reported health status. The goal of this regression is to understand which factors are related to subjective life expectancy, similar to Model 1 in Exhibit A1.1.
- **Model 2:** OLS Regression using the SCF data. Dependent variable is the error in the self-reported life expectancy compared to an estimate using the mortality model outlined in Appendix 1. Independent variables include age, gender, race, whether married, years of education, household income, whether currently smokes, and self-reported health status. The goal of this regression is to determine what factors are related to the accuracy of the life expectancy estimate.

The results of the regressions are included in Exhibit A3.1

Exhibit A3.1 SCF Regression Results

Model#	1	2
Dataset	SCF	SCF
Regression Type	OLS	OLS
Dependent Variable	Life Expectancy	Life Expectancy Error
Intercept	83.348***	16.508***
Age	0.170***	-0.076***
Male	-1.183**	0.314
Couple	-0.714	-0.005
Education Years	0.044	-0.115***
White/Non Hispanic	-2.328***	-1.542***
Smoker/Now?	-2.957***	0.522**
Income	-0.387**	-0.300***
Health — Excellent	4.160***	0.076
Health — Fair	-3.607***	0.739***
Health — Poor	-9.347***	1.860***
Observations	6,248	6,248
R ²	14.06%	9.80%

*** significant at .1% level, ** significant at 1% level, * significant at 5% level

Source: Survey of Consumer Finances.

Exhibit A4 OLS Regressions, Dependent Variable is the Retirement End Age Used in Financial Plan

	Coeff	t Stat	P-value
Intercept	91.040	1503.170	0.000
Age <30	0.240	3.100	0.000
Age 30-44	0.490	8.670	0.000
Age 55-64	0.400	8.080	0.000
Age >=65	1.010	14.940	0.000
Retirement Age <55	-0.580	-3.700	0.000
Retirement Age 55-59	0.110	1.910	0.060
Retirement Age 65-69	-0.020	-0.490	0.630
Retirement Age >=70	1.080	14.300	0.000
Goal <\$30k	-0.710	-11.260	0.000
Goal <\$30k-\$40k	-0.450	-8.140	0.000
Goal <\$50k-\$75k	0.390	7.080	0.000
Goal >=\$75k	1.450	25.240	0.000
Couple?	-0.290	-6.390	0.000
Male?	-0.600	-14.110	0.000
R ²	7.07%	—	—
Adjusted R ²	7.03%	—	—
Observations	31,211	—	—

Source: Anonymous Financial Planning Software.

About Morningstar's Investment Management Group

Morningstar's Investment Management group is a leading provider of discretionary investment management and advisory services. Guided by seven investment principles, the group is committed to focusing on its mission to design portfolios that help investors reach their financial goals. The group's global investment management team works as one to apply its disciplined investment process to all strategies and portfolios, bringing together core capabilities in asset allocation, investment selection, and portfolio construction. This robust process integrates proprietary research and leading investment techniques.

In addition to advisory services, the group's investment professionals build and manage model portfolios for financial advisors in the United States, United Kingdom, Australia and South Africa to create strategies that incorporate a wide variety of investment objectives.

*Includes assets under management and advisement for Morningstar Investment Management LLC, Morningstar Investment Services LLC, Morningstar Investment Management Europe Ltd., Morningstar Investment Management Australia Ltd., Ibbotson Associates Japan, Inc., Morningstar Investment Management South Africa (PTY) LTD, and Morningstar Associates, Inc. all of which are subsidiaries of Morningstar, Inc. Advisory services listed are provided by one or more of these entities, which are authorized in the appropriate jurisdiction to provide such services.

Disclosures

Morningstar Investment Management LLC is a registered investment adviser and subsidiary of Morningstar, Inc. The information, data, analyses, and opinions presented herein are provided as of the date written. Opinions expressed are subject to change without notice. This research is provided for informational purposes only. Before making any investment decision, please review your own personal situation and consider consulting financial and/or tax professionals regarding your unique situation.

This paper contains certain forward-looking statements. We use words such as "expects", "anticipates", "believes", "estimates", "forecasts", and similar expressions to identify forward looking statements. Such forward-looking statements involve known and unknown risks, uncertainties and other factors which may cause the actual results to differ materially and/or substantially from any future results, performance or achievements expressed or implied by those projected in the forward-looking statements for any reason. Past performance does not guarantee future results.



22 West Washington Street
Chicago, IL 60602 USA

©2020 Morningstar. All Rights Reserved. Unless otherwise provided in a separate agreement, you may use this report only in the country in which its original distributor is based. The information, data, analyses, and opinions presented herein do not constitute investment advice; are provided solely for informational purposes and therefore are not an offer to buy or sell a security; and are not warranted to be correct, complete, or accurate. The opinions expressed are as of the date written and are subject to change without notice. Except as otherwise required by law, Morningstar shall not be responsible for any trading decisions, damages, or other losses resulting from, or related to, the information, data, analyses, or opinions or their use. The information contained herein is the proprietary property of Morningstar and may not be reproduced, in whole or in part, or used in any manner, without the prior written consent of Morningstar. To license the research, call +1 312 696-6869.