The Predictive Validity of Subjective Mortality Expectations: Evidence from the Health and Retirement Study

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Abstract

Several recent studies suggest that individual subjective survival forecasts are powerful predictors of both mortality and behavior. Using fifteen years of longitudinal data from the Health and Retirement Study, we present an alternative view. Across a wide range of ages, predictions of in-sample mortality rates based on subjective forecasts are substantially less accurate than predictions based on population life tables. Subjective forecasts also fail to capture fundamental properties of senescence, including increases in yearly mortality rates with age. In order to shed light on the mechanisms underlying these biases, we develop and estimate a latent-factor model of how individuals form subjective forecasts. The estimates of this model's parameters imply that these forecasts incorporate several important sources of measurement error that arguably swamp the useful information they convey.

Keywords: Subjective survival forecasts, expectations, life tables

I. Introduction

Mortality expectations play a central role in individual decision-making. A host of behavioral models in economics and finance posit that mortality forecasts influence retirement planning, savings, portfolio choice, human capital accumulation, and investments in health. In spite of the importance of mortality forecasts, social scientists have not had access to individual-level data on these measures until recently. As a result, their usefulness for predicting mortality and behavior is largely unknown, both in absolute terms and relative to actuarial estimates based on published life tables.

In addition to their influence on individual decisions, mortality expectations also shape public policy, particularly the design of age-based entitlement programs such as Social Security and Medicare. Predictions of future mortality rates have taken center stage in the public debate about the future of these programs, with a loose consensus emerging that public expenditures will soar as age-specific mortality rates continue to fall (Leonhardt 2011). Although accurate mortality projections are essential for designing policy, mortality rates have been remarkably difficult to predict historically. As Oeppen and Vaupel (2002) document, past forecasts of mortality improvements have been systematically and substantially conservative. Most demographers project that mortality will continue to decline in the foreseeable future (Olshansky et al. 2005 is a notable exception), but there is little consensus about this projected decline's speed or magnitude. In an attempt to uncover additional sources of information that can potentially be useful to demographers in forming aggregate mortality forecasts, recent authors (including Hurd and McGarry 2002 and Perozek 2008) have explored the accuracy and validity of individual-level mortality forecasts obtained from survey data.

This study investigates the predictive power of subjective survival forecasts (SSFs) drawn from several cohorts of the Health and Retirement Study (HRS). We analyze forecasts of the likelihood of surviving to a range of “target ages”, with a focus on how these measures predict actual survival and how they evolve over time in response to new information. Unlike previous empirical studies of SSFs, our analyses make use of two unique features of the 2006 wave of the HRS. First, 2006 is the first year that original HRS respondents reach any of their target ages – the oldest members of the HRS cohort were 61 years old in the initial 1992 survey, which included questions about the likelihood of surviving to age 75, i.e., until roughly 2006. Therefore, data from the 2006 wave enable us to compare in-sample survival rates to subjective forecasts without imposing parametric assumptions on the shape of subjective survival curves. Second, subsamples of respondents to the 2006 wave answered detailed questions designed to gauge the reliability of their forecasts and to assess their knowledge of population life tables. We use responses to these questions to shed light on how individuals form SSFs and how they use new information to revise SSFs.

A large body of research has found strong links between SSFs and actual mortality. Hurd and McGarry (1995) and Manski (2004) showed that forecasts are correlated with behaviors that affect mortality, such as tobacco usage and regular exercise, while others found that forecasts predict in-sample mortality in short panels of the HRS (see, e.g., Hurd et al. 1998 and Hurd and McGarry 2002). Perhaps no study has produced more persuasive evidence of the predictive power of SSFs than that of Perozek (2008), who found that discrepancies between SSFs and published cohort life tables in 1992 actually predicted future revisions to the life tables. Specifically, men in the 1992 wave of the HRS were optimistic about their survival prospects relative to life tables, while women were pessimistic; in 2004, the Social Security Actuary revised the cohort life tables, raising estimates of male life expectancy while lowering estimates for women. Perozek (2008) interpreted the Actuary's revision as compelling evidence that individual SSFs predict future mortality rates better than life tables do.

In contrast to the findings of these previous studies, we present evidence that SSFs are only negligibly informative about future mortality rates. Across a wide range of ages in the HRS, predictions of in-sample survival based on SSFs are far less accurate than predictions based on population life tables. The SSFs systematically understate the likelihood of living to relatively young ages (such as age 75) while overstating the likelihood of surviving to ages 85 and beyond. We show that these forecast errors are consistent with the notion that, at a given point in time, individuals do not recognize that yearly death rates increase with age, a fundamental pattern of senescence.

In light of the systematic biases apparent in the SSFs, we develop and estimate a latent-factor model of how individuals form subjective forecasts. A key feature of this model involves the relationship between SSFs and "cohort subjective survival forecasts" (CSSFs), which are individuals' beliefs about the survival prospects of others of their age and gender, assessed in the 2006 wave of the HRS. The resulting estimates suggest that the discrepancies between the SSFs and actuarial forecasts arise primarily from noise in the SSFs, which accounts for substantially more of the across-respondent variation in the SSFs than do differences across individuals in actual survival prospects. The estimates also imply that individuals' beliefs about others' chances of survival exhibit the same biases found in the SSFs; for example, the CSSFs also systematically understate the likelihood of living to relatively young ages while overstating the likelihood of surviving to relatively old ages.

In Section II below, we describe the HRS, with a focus on the various subjective survival measures available in these data. In Section III, we study the relationship between SSFs and in-sample survival in the HRS. In Section IV, we develop and test an explanation for the systematic bias in SSFs, based on the notion that, at a point in time, individuals do not appear to realize that their own yearly mortality rates will steadily increase in the future as they age. Section V presents the latent-factor model of individual and cohort subjective survival forecasts, and Section VI concludes with a research agenda.

II. Subjective Survival Forecasts in the Health and Retirement Study

The HRS is a national panel study of four different cohorts. The original HRS cohort, a nationally representative sample of the non-institutionalized population born between 1931 and 1941, was initially interviewed in 1992, with follow-up interviews every two years thereafter. A separate study, the Asset and Health Dynamics Study (AHEAD), began in 1993 as a sample of those born before 1924. In 1998, the two studies were combined, and two additional cohorts were added to the sampling design. The Children of the Depression (CODA) cohort filled the 7-year age gap between the original HRS and AHEAD cohorts by targeting those born between 1924 and 1930, and the War Baby (WB) cohort targeted those born between 1942 and 1947. From 1998 forward, the HRS sampling frame includes all four cohorts, representing the population of Americans over age 50 who do not live in institutional settings such as nursing homes.[1] The HRS has also included an oversample of African-Americans, Hispanics, and Florida residents since its inception, and spouses and domestic partners of target respondents are also interviewed.

[1] This sampling design is intended to match that of the over-50 population represented by the Current Population Survey (CPS) in order to facilitate comparisons between the two data sets.

For the purposes of this study, the key components of the HRS are responses to variants of the following question:

> *"On a scale from 0 to 100, where 0 is no chance and 100 is absolutely certain, what are the chances that you will live to age **X** or older?"*

Respondents under age 65 are asked this question for X = 75 in all waves and for X = 85 in the 1992, 1994, 1996, 1998 and 2006 waves. We denote individuals' responses to these questions as P_{75} and P_{85}, respectively (we suppress individual subscripts to economize on notation). Respondents aged 65 and over answer a separate question about the likelihood of living roughly another 11 to 15 years. Specifically, those aged 65 to 69 are asked about the likelihood of surviving to age 80, those aged 70 to 74 are asked about the likelihood of surviving to age 85, and so on. We denote these 11- to 15-year ahead forecasts as P_{11}.

Do Subjective Survival Forecasts Predict Future Mortality Rates?

Table 1 presents averages of P_{75} and P_{85} by gender and survey wave for all HRS respondents aged 50 to 65, along with the corresponding averages implied by each year's Vital Statistics period life tables published by the National Center for Health Statistics. Relative to the life tables, in 1992 men held relatively accurate expectations about the likelihood of survival to age 75 while women were pessimistic: the averages of P_{75} were 62.53 for men and 65.80 for women, compared to 61.30 and 74.45, respectively, according to the life tables. In making these comparisons, note that period life tables do not capture the actual mortality profile facing *any* cohort if age-specific mortality rates vary over time. In fact, the steady decline in age-specific mortality rates in the U.S. since 1992 implies that the 1992 life tables understate actual survival probabilities, making the pessimism among women even more surprising.[2] We weight data after 1992 in order to generate constant gender-specific age distributions across survey waves. This procedure has the effect of standardizing all later years' age distributions to match that found in the 1992 survey.[3] This standardization process highlights the steady decline in mortality rates since 1992 – with a constant age distribution within gender, the actuarial survival forecasts evolve over time only because of changes in yearly life tables. Appendix Table 1, which presents results based on the raw (non-standardized) data, shows very similar patterns to those found in Table 1.

Based on the SSFs in the 1992 wave of the HRS, Perozek (2008) concludes that individuals anticipate future changes in mortality, but several features of Table 1 are inconsistent with this interpretation. Among women, the 1992 average of P_{75} is much lower than the average based on 1992 life tables, consistent with a belief that age-specific death rates would sharply *increase* after 1992. In reality, death rates steadily declined during this period for both men and women. Additionally, neither gender's forecasts of survival to age 75 increased from 1992 to 2006. For men, the average of P_{75} declined from 62.53 to 59.10 (this decline is statistically

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[2] Yearly life tables record the probability of surviving to age $x+1$ conditional on reaching age x, based on actual mortality rates in that year. Letting $d_{x,t}$ be the number of people who die between age x and age $x+1$ in a given year t and letting $l_{x,t}$ be the number of people alive at age x in that year, this probability equals $(1 - (d_{x,t}/l_{x,t})) \equiv 1 - q_{x,t}$. A researcher might use year t life tables to compute a probability of living to age S conditional on reaching age R as $\prod_{j=R}^{S-1}(1-q_{j,t})$, but the actual *ex post* survival probability equals $\prod_{j=R}^{S-1}(1-q_{j,t+R-j})$. As an example, one might calculate the probability that a person aged 60 in 1992 lives to age 62 by multiplying the 1992 one-year survival rate for those aged 60 by the 1992 one-year survival rate for those aged 61. This will understate the true 2-year survival rate if the probability of living to age 62 conditional on reaching age 61 increases between 1992 and 1993. More generally, survival probabilities based on a given year's life tables will understate the true probability of survival to age x if age-specific survival probabilities increase over time.

[3] Among respondents of gender g in year t, the sample fraction that is age x is $\Pr(\text{age} = x \mid g, t)$. Therefore, in order to match the within-gender age distribution in 2006 to that found in 1992, for example, respondents of gender g aged x are weighted by $\frac{\Pr(age = x \mid g, t = 1992)}{\Pr(age = x \mid g, t = 2006)}$. In Table 1, we report weighted survival probabilities for all years in the table based on the age distribution among HRS respondents in 1992.

significant at conventional levels; $t = 4.51$), even though actual death rates were falling steadily. As a result, the downward bias in individual forecasts has grown over time. A literal interpretation of subjective forecasts as predictions of future mortality implies that in 2006, both men and women anticipated substantial increases in future death rates at ages below 75.

Panel B of Table 1 presents average values of P_{85} in the 1992-1998 and 2006 waves. In contrast to Panel A, men are optimistic about their prospects for survival in all years. Women are neither systematically optimistic nor pessimistic, with higher survival forecasts than implied by life tables in three of the five years. As was the case in Panel A, average SSFs remained roughly constant over this period in spite of increases in actuarial survival rates, particularly for men. In all years, men and women's SSFs imply much flatter survival profiles than those based on life tables; this pattern is easiest to see for 2006 male respondents, who substantially underpredict P_{75} and overpredict P_{85}.

Men's optimistic forecasts of P_{85} in 1992, which are seemingly prescient because of the ensuing increase in actuarial survival rates from 26.99 to 32.74 percent, are the principal mechanisms driving Perozek's interpretation that men accurately forecasted increases in their life expectancy. However, a strict interpretation of men's subjective forecasts as predictions of future survival rates again implies an unusual prediction: the stability of the average of P_{85} from 1992 to 2006 implies that men aged 50 to 65 in 2006 are no more likely to survive to age 85 than those aged 50 to 65 in 1992. Such stagnation would represent an abrupt end to a steady decline in mortality rates that has lasted for more than a century.[4] While we cannot evaluate this

[4] Oeppen and Vaupel (2002) show that "best-performance" longevity, i.e., the life expectancy of the longest-lived ethnicities or nationalities, has steadily increased by roughly 2.5 years per decade since 1840. While other authors such as Olshansky et al. (2005) predict stagnation and even declines in longevity within the next century, Oeppen and Vaupel (2002) demonstrate that such predictions have commonly been made (and subsequently proven wrong) in the past 160 years, arguing that there is no compelling reason to believe that the trend should end now.

prediction using current data, we can directly assess the accuracy of SSFs by analyzing HRS sample members' own mortality experiences.

III. Subjective Survival Forecasts and In-Sample Survival in the HRS

As noted above, several previous studies have analyzed in-sample survival rates in the HRS, finding that measures such as P_{75} and P_{85} predict survival from 1992 to 1994 (Hurd and McGarry 1995) and from 1992 to 1998 (Hurd et al. 2002). Recent releases of the data provide an opportunity to evaluate subjective forecasts more closely because some individuals have reached the target ages of their forecasts. Specifically, for AHEAD cohort members aged 74, 79, and 84 in 1993, the P_{11} target age corresponded to a survivor's actual age in 2004.[5] Similarly, for the oldest HRS cohort members, who are 65 in 1996, P_{75} measures the likelihood of surviving to 2006. As a result, it is now possible to assess the accuracy of subjective probabilities nonparametrically, without specifying a functional form of the underlying hazard function.

Figure 1 presents age-specific averages of P_{75} for those aged 60 to 65 in the 1996 HRS and of P_{11} for those aged 70 to 85 in the 1993 AHEAD, with both series labeled as "Subjective Forecasts". The gap in the series between ages 65 and 70 reflects the gap in the age coverage of the original HRS and AHEAD cohorts.[6] The figure also includes predicted survival rates to the target ages based on "initial year" life tables (1996 for the original HRS cohort and 1993 for the AHEAD cohort) and "target year" life tables (2006 for the HRS and 2004 for the AHEAD), and the actual survival rates as of the target year based on HRS coding of respondents' vital status.

[5] In the 1995 wave of the AHEAD, individual respondents were asked about the same target ages as they were in 1993, so that those aged 72-76 were given a target age of 85, those aged 77-81 given a target age of 90, and so on. In all following waves, the mapping between a respondent's age and the target age reverted back to that used in 1993, e.g., those aged 70-74 were given a target age of 85.

[6] The 1993 AHEAD included persons under age 70 who were spouses of respondents who were 70 or over, but we exclude these individuals from the figure because the resulting samples are both small and non-representative of the U.S. population at these ages.

The saw-tooth patterns of both series based on life tables reflect the discontinuities in target ages between initial ages 74 and 75, 79 and 80, and 84 and 85. Appendix Table 2 provides the values of all four series for each initial age.

As the figure shows, survival rates steadily decline in initial age. Approximately 61 percent of respondents aged 70 in 1993 survived until 2004, compared to only 29 percent of those aged 80. Importantly, the in-sample survival curve lies between the curves based on the two life tables at the initial ages of 65, 74, 79, and 84, which are the initial ages at which surviving respondents reach the target age in the target year (vertical lines denote these initial ages in the figure). This pattern implies that population life tables are remarkably accurate in predicting in-sample survival, reflecting that the HRS and AHEAD samples are nationally representative: *population* survival rates between years t and $t+k$ will lie between those predicted by year t and year $t+k$ life tables if death rates are monotonically decreasing over time. At other initial ages, the survival curve is typically higher than the life table curves because survivors have not yet reached their target age. For example, an individual aged 70 in 1993 has only reached age 81 in 2004, but both the actuarial and subjective forecasts refer to survival to age 85.

Figure 1 also shows that the SSFs perform poorly in predicting in-sample survival. Specifically, SSFs understate survival by roughly 11 percentage points among those aged 65 in the 1996 HRS and substantially overstate survival for those aged 80 and above. The survival rate among 84-year-olds is less than one-fourth as high as the survival rate among 65-year-olds (18 percent versus 78 percent), but the former group's average SSF is more than half as large as the latter's (36 percent versus 67 percent). By this metric, the SSFs are less than half as steep with respect to age as are actual survival rates, a phenomenon we describe below as "flatness bias". Note that we pool data from both genders in producing the figure (and in all analyses below), but gender-specific SSFs are also substantially flatter than the corresponding in-sample survival rates.

As further evidence on the relative predictive power of SSFs and life tables, Table 2 presents estimates from individual-level probit models of survival to the target year as a function of the initial-year SSFs and actuarial forecasts based on initial-year life tables. Column (1) shows estimated marginal effects from specifications in which the estimation samples include all respondents who, if they survived, would have reached their target age by the target year: those aged 65 in 1996 and those aged 74, 79, and 84 in 1993. The coefficient on the subjective forecast is 0.144, implying that a 1 percentage-point increase in SSFs is associated with only a 0.144 percentage-point increase in actual survival.[7] In contrast, actual survival mirrors variation in life table-based forecasts almost exactly: a one percentage-point increase in the life table forecast is associated with a 1.055 percentage-point increase in actual survival (this estimate is statistically indistinguishable from 1).

Column (2) of the table adds controls for respondents' marital status, race, ethnicity, living arrangements, assets, income, education, and body mass index. For space considerations, we do not report the effects of these controls in the table, but the two factors which have the strongest effects on survival are household living arrangements and education – a respondent living with a partner is roughly 7 percentage points more likely to survive than one who lives alone, and college graduates are roughly 8 percentage points more likely to survive than those who did not complete high school. In contrast, gender does not significantly affect survival in

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[7] By comparison, Hurd and McGarry (2002) estimate that a 1 percentage-point increase in the SSFs is associated with a 0.016 percentage-point increase in the likelihood of actually surviving from wave 1 to wave 2 of the HRS. This estimate is much smaller than that found here for two reasons: first, Hurd and McGarry's (2002) dependent variable captures survival over only a 2-year period, compared to up to 14 years in the models considered above, and second, their sample includes only those younger than 65 in wave 1. As a result, the probability of death in their estimation sample was roughly 1.7 percent, compared to 53 percent in the sample used in columns (1) and (2) of Table 2 and 27 percent in the sample used in columns (3) and (4).

these models, as the inclusion of the actuarial forecasts captures the female longevity advantage. Most importantly for our purposes, the inclusion of these controls does not substantially change the coefficients on either the subjective or the actuarial forecasts.

Columns (3) and (4) of the table show estimates from models in which the estimation sample includes all initial-year respondents, i.e., all HRS cohort members aged 65 and younger in 1996 and all AHEAD cohort members aged 70 or older in 1993. These models again show that the actuarial forecasts are much more predictive of survival than are the SSFs.[8] The marginal effects of the actuarial forecasts are approximately one in all specifications. We return to this issue in Section V below, where we consider why actuarial forecasts predict survival better than do SSFs in the context of a latent factor model of survival beliefs.

Taken together, Figure 1 and Tables 1 and 2 provide strong evidence that SSFs do not predict group-level mortality as well as population life tables do, in contrast to the conclusions of Perozek (2008). SSFs in 1992 did not predict future changes in mortality rates, and they became steadily less accurate over time. More importantly, SSFs are flatter with respect to age than are actuarial forecasts and in-sample survival rates, implying that individuals systematically understate their chances of surviving to relatively young ages and overstate their chances of surviving to relatively old ages. This flatness bias may largely stem from the fact that individuals report their own probabilities of survival, rather than estimates of the survival prospects of their cohort.[9] In Section V below, we evaluate this possibility by analyzing cohort

[8] The estimates shown in Table 2 are not necessarily inconsistent with the findings of authors such as Smith et al. (2001), who argue that SSFs are useful for predicting individual variation in mortality. Conditional on a respondent's age and gender, SSFs are more informative than forecasts based on life tables *by definition*, because published life table values are constant within age-gender cells.

[9] Although it is unlikely that respondents consult life tables when thinking about their own survival prospects, this information is publically available, as the Centers for Disease Control provide detailed age- and gender-specific population life tables on their website: http://www.cdc.gov/nchs/products/life_tables.htm.

subjective survival forecasts directly, but we first turn to the importance for flatness bias of the apparent inability of individuals to understand that mortality risk increases with age.

IV. Do Survey Respondents Recognize That Death Rates Increase with Age?

The flatness bias in subjective survival forecasts is not unique to HRS respondents, as Hamermesh (1985) documented a similar phenomenon in a sample of economists from the early 1980s. Mirowsky (1999) also found that optimism about survival increased with age in the Aging, Status, and the Sense of Control survey.[10] As Hamermesh (1985) noted, flatness bias is surprising if SSFs represent rational extrapolations of current life tables into the future. Specifically, if respondents anticipate future increases in survival rates, young respondents' subjective forecasts should be "optimistic" relative to current life tables, and that this relative optimism will decline with age. As a result, SSFs should be steeper with respect to age than are actuarial forecasts, in contrast to the flatness bias apparent in the HRS.

Here we present an explanation for flatness bias based on the hypothesis that individuals, at a given point in time, do not recognize that yearly death rates increase with age. [11] Consider a discrete-time model of mortality in which the probability that an individual aged x dies before reaching age $x+1$ is denoted as q_x. The probability of surviving to age x_2 given survival until age x_1 is given by:

(1) $$\Pr(\textit{survive to age } x_2 \mid \textit{survive to age } x_1) = \prod_{j=x_1}^{x_2-1}(1-q_j).$$

[10] In describing possible reasons why optimism increases with age, Mirowsky (1999) speculated that "…the simplest explanation is that continuing survival encourages greater optimism at older ages because it seems increasingly remarkable."

[11] It is important to distinguish this phenomenon, which is apparent among individuals of a given age forecasting their survival prospects to two different points in the future, from changes in forecasts over time for an individual. This latter source of variation does imply that individuals recognize, over time, that death rates increase with age. We return to this distinction at the end of this section.

If age-specific death rates are constant at the rate q, then this expression simplifies to

(2)
$$\Pr(\textit{survive to age } x_2 \mid \textit{survive to age } x_1) = \prod_{j=x_1}^{x_2-1}(1-q) = (1-q)^{x_2-x_1}.$$

For example, for a person aged 65, the probability of surviving to age 75 equals $(1 - q)^{10}$, and the probability of surviving to age 85 is $(1 - q)^{20}$, so that $P_{85} = P_{75}^2$. More generally, if individuals form subjective forecasts based on the belief that yearly death rates do not increase with age, then

(3)
$$P_{85}^{(75-age_i)} = P_{75}^{(85-age_i)},$$

where age_i is the age of respondent i at the time of the forecast. Taking logarithms of (3) and rearranging,

(4)
$$\log(P_{85})_i = \left[\frac{85-age_i}{75-age_i}\right]\log(P_{75})_i.$$

Equation (4) forms the basis of a test of the hypothesis that individuals, at a given point in time, believe that yearly death rates are constant with respect to age, which we refer to hereafter as the "constant hazard hypothesis". To operationalize this test, we estimate the following linear model:

(5)
$$\log(P_{85})_i = \alpha + \sum_{j=50}^{65}\beta_j\left[D_{ij}\times\log(P_{75})_i\right] + u_i,$$

where j indexes ages from 50 to 65, D_{ij} denotes a vector of dummy variables (one for each age j) that each equal one when $age_i = j$ and zero otherwise, and u_i represents individual variation in $\log(P_{85})$ that is unrelated to $\log(P_{75})$.[12] The constant hazard hypothesis implies specific values for each β_j: for

[12] The use of a logarithmic specification introduces problems when P_{75} and / or P_{85} equal zero. In practice, we set P_{85} equal to 0.01 when P_{75} is positive but P_{85} equals zero. We drop observations for which both P_{75} and P_{85} equal zero, but the results presented below in Table 3 are insensitive to instead setting both P_{75} and P_{85} equal to 0.01 in these cases.

example, it predicts that β_{65} equals 2.0 (= (85 – 65) / (75 – 65)) and β_{64} equals approximately 1.91 (= (85 – 64) / (75 – 64)).

To get a sense of the intuition underlying the constant hazard hypothesis, consider the distribution of $[P_{85} - (P_{75})^2]$ among HRS respondents aged 65. For 433 of these 896 respondents, $[P_{85} - (P_{75})^2]$ is nonnegative, which implies weakly *decreasing* yearly death rates with age. For example, a 65-year-old man who reports $P_{75} = 0.8$ and $P_{85} = 0.7$, so that $[P_{85} - (P_{75})^2] = 0.06$, believes that his 10-year-ahead survival probability is 80 percent at age 65 and 87.5 percent (= 0.7 / 0.8) at age 75. Among 65-year-olds, the mean value of $[P_{85} - (P_{75})^2]$ is –0.04, which is statistically indistinguishable from zero ($p = 0.19$).

Table 3 presents evidence about the constant hazard hypothesis based on estimates of equation (5). Column (1) of the table shows estimates of β_j from OLS regressions for $j = 50$, 55, and all ages from 60 to 65 (results for other ages, excluded to economize on space, are available upon request). A one-percent increase in P_{75} is associated with a 1.17 percent increase in P_{85} among 50-year-old respondents, with a standard error of 0.09. The corresponding value implied by the constant hazard hypothesis is 1.40, as shown in column (3). In column (4), P_{75} and P_{85} are taken from the relevant year's life tables rather than from the subjective forecasts. The estimate of 2.33 is substantially larger than that implied by the constant hazard hypothesis, reflecting that death rates increase with age in the population.

The remaining estimates of β_j in column (1) are all significantly smaller than the corresponding values implied by the constant hazard hypothesis. Again, these patterns suggest that individuals believe that death rates decrease with age. By contrast, the estimates in column (4) are substantially larger than those in column (3), and they increase with the age of the respondents. At age 65, the estimate in column (1) is 1.12, compared to 3.03 in column (4).

The overall patterns of Table 3 suggest that, at a given point in time, HRS respondents fail to understand that mortality rates increase with age. In fact, they imply that respondents believe that mortality rates *decrease* with age; specifically, those younger than 65 appear to believe that annual death rates are higher at ages below 75 than at ages between 75 and 85. We are wary to accept this interpretation at face value, though, because measurement error might play a pivotal role in producing the estimates in Table 3. Such measurement error plays a prominent role in previous research on SSFs, particularly in the context of "focal responses", which are forecasts of exactly 0, 50, or 100 percent (see, e.g., Lillard and Willis 2001; Kézdi and Willis 2003; Gan et al. 2005). Unlike reporting error in an objectively measured variable, the concept of error in subjective forecasts is unintuitive because the definition of the underlying "true" value of the variable is not straightforward; for example, it is difficult to characterize an individual's true belief about his own survival prospects if it differs from what he reports in a survey.[13]

While it is difficult to define measurement error in subjective data, demonstrating its existence is relatively straightforward. For example, Bertrand and Mullainathan (2001) show that subjective responses vary substantially across repeated questions spaced closely together in time. The 2006 wave of the HRS provides an opportunity to use such variability as a measure of the error in subjective data. Specifically, a 10 percent random sample responded to a supplemental data module that included the question, "*What are the chances you will live to age **X**?*" which is identical to P_{75} for those younger than 65 and identical to P_{11} for those aged 70 and

[13] A large experimental literature examines the sensitivity of survey responses to various factors, including the phrasing of questions, the order in which questions are asked, and interviewer cues on the social desirability of particular responses. This literature finds that subjective survey responses are particularly sensitive to these factors, possibly because subjective beliefs cannot be verbalized and may not even exist in a coherent form. Tanur (1992) and Sudman et al. (1996) provide excellent reviews of the experimental evidence.

over. As a result, respondents in this subsample provided two comparable SSFs over the course of the approximately hour-long interview.

In order to use the repeated forecasts to analyze the role of measurement error, consider a model in which the logarithm of reported survival forecasts, $\log(P_{75})$, equals one's "true" belief about longevity, $\log(P_{75})^*$, plus error (ε) that possibly reflects an inability to verbalize this belief. We can then write the two 2006 survey responses as

(6)
$$\begin{aligned}\log(P_{75})_{i1} &= \log(P_{75})_i^* + \varepsilon_{i1} \\ \log(P_{75})_{i2} &= \log(P_{75})_i^* + \varepsilon_{i2},\end{aligned}$$

where $\log(P_{75})_{i1}$ denotes an individual's response to the full-sample HRS question and $\log(P_{75})_{i2}$ represents the same individual's response in the supplemental module. Under the classical measurement error assumptions that ε_{i1} and ε_{i2} are orthogonal to each other and to the true beliefs, the slope coefficient from a simple regression of $\log(P_{75})_{i2}$ on $\log(P_{75})_{i1}$ converges to $\frac{\text{var}(\log(P_{75})_i^*)}{\text{var}(\log(P_{75})_i^*) + \text{var}(\varepsilon_{i1})}$, which is the fraction of the variance of $\log(P_{75})_{i1}$ that reflects the variance in the true beliefs. Importantly, this ratio also represents the extent to which measurement error attenuates $\hat{\beta}_{j,OLS}$, the OLS estimate of β_j based on equation (5):

(7)
$$\text{plim}(\hat{\beta}_{j,OLS}) = \left[\frac{\text{var}(\log(P_{75})_i^*)}{\text{var}(\log(P_{75})_i^*) + \text{var}(\varepsilon_{i1})}\right]\beta_j .$$

Based on the 587 individuals with valid responses for both $\log(P_{75})_{i1}$ and $\log(P_{75})_{i2}$ in 2006, the estimate of $\frac{\text{var}(\log(P_{75})_i^*)}{\text{var}(\log(P_{75})_i^*) + \text{var}(\varepsilon_{i1})}$ is 0.714 (0.025), implying that the estimates in column (1) of Table 3 are biased downward by 28.6 percent. Therefore, in column (2) we report rescaled estimates of β_j that are the OLS estimates in column (1) divided by 0.714.[14] These rescaled estimates are larger than the estimates in column (1) by construction, but they still provide little evidence that respondents understand that death rates increase with age. In particular, they are insignificantly different from the values in column (3) among those younger than 60 and significantly smaller than the values in column (3) for those aged 62 to 65.

In summary, the results of Table 3 imply that SSFs are poor predictors of aggregate survival partly because survey respondents, at a point in time, do not understand that death rates increase with age. As a result, they overstate the likelihood of dying at young ages while understating the likelihood of dying at relatively old ages. At first glance, this hypothesis appears inconsistent with the patterns in Figure 1 above, which showed that 11- to 15-year-ahead SSFs decline with age, i.e., that subjective mortality risk increases with age. However, it is important to emphasize that these two sets of findings stem from two different sources of variation in SSFs. The first involves variation across target ages for a particular individual at a given age below 66, while the second involves variation across individuals of different ages, many of whom are in their 70s and 80s. The discrepancy implies that individuals learn that mortality risk increases with age *as they age*. In auxiliary analyses, we find additional evidence in support of this inference: estimates from models of SSFs as a function of age and individual-specific fixed effects indicate that SSFs to a given target age decline with age.[15] The failure of SSFs to capture one of the most basic properties of actuarial survival estimates – that they increase in age for a given target age – likely reflects that individuals receive new health

[14] As noted by an anonymous reviewer, the item-reliability estimate of 0.714 is roughly comparable to that found among other subjective measures, such as self-rated health on a 5-point scale from "excellent" to "poor". Zajacova and Dowd (2012) estimated reliability of self-rated health at 0.75 in NHANES data, and Crossley and Kennedy (2002) find similar reliabilities in the Australian National Health Survey.

[15] In models that include individual fixed effects, $SSF_{it} = \alpha + \beta Age_{it} + \mu_i + v_{it}$, where Age_{it} refers to individual i's age at time t and μ_i denotes the fixed effects, we estimate that β = -0.068 (0.024) when the SSF is P_{75} and -0.072 (0.031) when the SSF is P_{85}. The corresponding estimates are 0.875 (0.002) and 0.602 (0.002), respectively, when we instead use actuarial survival probabilities as dependent variables.

information over time which causes them to revise their survival forecasts downward. In light of this failure, we turn next to describing more formally how individuals form their SSFs and how these forecasts evolve in response to new information.

V. A Model of Individual and Cohort Subjective Survival Forecasts

The results thus far have hinted at the underlying relationships between SSFs and actuarial survival forecasts. In this section, we explicitly model these relationships in order to shed light on how individuals think about their chances of survival, how they report these beliefs to interviewers, and how these beliefs might differ from how they think about others' chances of survival. To do so, we first consider a source of information found only in the 2006 wave of the HRS.

Cohort Subjective Survival Forecasts: Can Individuals Predict Others' Deaths?

In 2006, a supplemental module administered to 10 percent of HRS respondents included a question designed to measure their knowledge of population life tables:

> *"Out of a group of 100 [men/women] your age, how many do you think will survive to the age of **X**?"*

The target age ***X*** equals 75 for those younger than 65 and equals the P_{11} target age for those 65 and older. These "cohort subjective survival forecasts" (CSSFs) are positively related to individuals' own SSFs, with a simple correlation of 0.30 (t = 8.64). Both sets of forecasts are positively correlated with actuarial forecasts: the estimated slope from a simple regression of CSSFs on actuarial forecasts is 0.68 (t = 25.03), and the estimated slope from a simple regression of SSFs on actuarial forecasts in the same sample is 0.48 (t = 12.48).

Figure 2 shows age-specific averages of CSSFs, SSFs, and actuarial survival estimates for the 1348 supplemental module respondents. Note that the CSSFs exhibit the same flatness bias as the SSFs, with the CSSF curve lying far below the actuarial estimates at relatively young ages but lying slightly above the actuarial estimates at ages above 80. The CSSF curve appears to be essentially a “shifted down” version of the SSF curve, reflecting that respondents’ own survival forecasts are 9.3 percentage points higher than their CSSFs, on average.

Actuarial Forecasts, Cohort, and Own Subjective Survival Forecasts

In order to model the relationships between the SSFs, CSSFs, and actuarial survival forecasts, we must first introduce some notation. Denote actuarial survival forecasts as A_i. An individual’s cohort subjective survival forecast, $CSSF_i$, can be written as the sum of A_i, his error in guessing A_i (denoted as g_i), and an additional component, v_i, which can be interpreted as a random error that captures his inability to precisely express his beliefs to an interviewer. This last component is analogous to the “measurement error” in subjective forecasts described in the previous section. Similarly, we can write SSF_i as the sum of A_i, g_i, and two additional components. The first, d_i, represents the individual’s true deviation from A_i. The second, e_i, represents both the individual’s random error in guessing d_i and his inability to express this quantity. We can then write the SSFs and CSSFs as

$$\begin{aligned} SSF_i &= A_i + g_i + d_i + e_i \\ CSSF_i &= A_i + g_i + v_i. \end{aligned} \tag{8}$$

In practice, we assume that the error components e_i and v_i are orthogonal. We do not make the same restriction about g_i and d_i, because it is plausible that individuals “project” their own survival prospects onto their CSSFs, inducing correlation between g_i and d_i. To capture this possibility, we model both g_i and d_i as a function of a latent factor θ_i:

$$g_i = \lambda_g \theta_i \qquad (9)$$
$$d_i = \lambda_d \theta_i,$$

where θ_i is a standard normal random factor and λ_d and λ_g are factor loadings.[16]

The joint distribution of SSF_i and $CSSF_i$ is not sufficient to identify the components of the model described by (8) and (9) – there are four unknown parameters (λ_d, λ_g, var(e_i), and var(v_i)) but only three observable second moments (var(SSF_i), var($CSSF_i$), and cov(SSF_i, $CSSF_i$)). Fortunately, the 2006 wave of the HRS contains another unique source of information that can help to identify these components: "revised" subjective survival forecasts. Specifically, after a respondent reveals his CSSF (which is essentially his guess of A_i), the interviewer tells him the true value of A_i, based on 2003 life tables:

> *"Now, suppose I told you that according to statistics, on average about [#] out of 100 [men/women] your age should live to age **X**."*

After giving the respondent this information, the interviewer then asks the respondent for a revised SSF, using the same target ages as before. We denote this revised forecast as $RSSF_i$. Like SSF_i, we model $RSSF_i$ as the sum of A_i, d_i, and an error that represents random error in guessing d_i and the inability to express d_i to an interviewer (u_i). Unlike SSF_i, however, $RSSF_i$ does not incorporate error in guessing A_i because respondents have just learned the value of A_i.

With the inclusion of the equation for $RSSF_i$, the model becomes

$$SSF_i = A_i + g_i + d_i + e_i$$
$$CSSF_i = A_i + g_i + v_i \qquad (10)$$
$$RSSF_i = A_i + d_i + u_i.$$

[16] This structure allows for positive, negative, or zero correlation between g_i and d_i. Specifically, var(g_i) = λ_g^2, var(d_i) = λ_d^2, and cov(d_i, g_i) = $\lambda_d\lambda_g$.

Under the assumption that the response error u_i is orthogonal to all other components of the model, we can write the six observed second moments as follows:

(11)
$$\begin{aligned}
\text{var}(SSF_i) &= \text{var}(A_i) + \lambda_g^2 + \lambda_d^2 + 2\lambda_d\lambda_g + \text{var}(e_i) \\
\text{var}(CSSF_i) &= \text{var}(A_i) + \lambda_g^2 + \text{var}(\nu_i) \\
\text{var}(RSSF_i) &= \text{var}(A_i) + \lambda_d^2 + 2\lambda_d\lambda_g + \text{var}(u_i) \\
\text{cov}(SSF_i, CSSF_i) &= \text{var}(A_i) + \lambda_g^2 + \lambda_d\lambda_g \\
\text{cov}(SSF_i, RSSF_i) &= \text{var}(A_i) + \lambda_d^2 + \lambda_d\lambda_g \\
\text{cov}(CSSF_i, RSSF_i) &= \text{var}(A_i) + \lambda_d\lambda_g .
\end{aligned}$$

These six equations are functions of five unknown parameters (λ_d, λ_g, $var(e_i)$, $var(v_i)$, and $var(u_i)$), so this system does not have an exact solution. Therefore, we estimate the parameters by minimizing the sum (across the six equations) of the squared differences between the theoretical and observed variances and covariances.[17] We bootstrap all standard errors based on 500 replicate samples drawn with replacement from the original estimation sample.

Table 4 presents the estimates of this latent factor model. The first two columns list the observed second moments involving the three forecasts. The variance of the SSFs is larger than the variance of the CSSFs, as the SSFs incorporate information about an individual's own health and survival (d_i). Note also that the variance of the revised SSFs is much smaller than the variance of the SSFs, consistent with the view that some of the variation in the SSFs stems from uncertainty about cohort survival; when respondents learn A_i, their beliefs about their own survival become more precise.

The second set of columns presents the estimated parameters. The estimate of λ_d is 16.68 (0.85), which implies that the estimated variance of d_i is 278.21 (28.15). Similarly, the estimate of λ_g is 7.06 (0.94), which implies that the estimated variance of g_i is 49.86 (30.21). The

[17] More concretely, we define $m_1 = \{var(SSF_i) - var(A_i) - \lambda_g^2 - \lambda_d^2 - 2\lambda_g\lambda_d - var(e_i)\}^2$, $m_2 = \{var(CSSF_i) - var(A_i) - \lambda_g^2 - var(v_i)\}^2$, and so on. We then choose the 5 parameters to minimize $m_1 + m_2 + m_3 + m_4 + m_5 + m_6$.

estimates of the other components illustrate that response errors play important roles in all of the subjective forecasts. Specifically, the estimate of var(e_i) is 361.10 (31.70), substantially larger than the estimate of $var(d_i)$. This implies that, relative to actuarial survival estimates, the SSFs add more noise (represented by e_i) than genuine individual-specific information about health and survival prospects (represented by d_i). In fact, the variation in d_i represents only 34.48 percent of the total variation in SSFs, net of variation in actuarial survival rates. The remaining variation is due to e_i, g_i, and the factor θ_i that influences both d_i and g_i. Similarly, the estimated variance of v_i is 379.23 (23.28), which is striking because it implies that nearly 83 percent (= 379.23 / 458.84) of the variance of $CSSF_i$ reflects errors in expressing probabilities. This is perhaps not surprising given that the between-respondent variance of A_i is 29.73, or only 6.48 percent of the variance of $CSSF_i$.

Overall, the estimated parameters reinforce the notion that individuals' subjective survival forecasts incorporate a substantial amount of noise. This noise includes uncertainty about one's own survival prospects, uncertainty about the survival prospects of one's cohort, and measurement error that reflects an inability to express these quantities to survey enumerators. Much of the previous research on SSFs has speculated that they are more useful than actuarial forecasts because SSFs contain information about one's own mortality risk, which is necessarily absent from actuarial forecasts. However, the estimates in Table 4 suggest that SSFs incorporate a great deal of random error that arguably swamps the information content contained in d_i. This is likely a key reason why actuarial survival forecasts outperform SSFs for predicting actual survival.[18]

[18] Noise in SSFs also plays a large role in the results of Table 2 above, which showed that actuarial forecasts outperform SSFs in models of in-sample survival. As expression (10) shows, SSFs net of actuarial forecasts (SSF_i – A_i) equal $g_i + d_i + e_i$, so the coefficient on SSF_i in a linear regression of survival (Y_i) on SSF_i and A_i will converge to cov(Y_i, $g_i + d_i + e_i$) / var($g_i + d_i + e_i$). If g_i and e_i are unrelated to actual survival, one can use the estimates in Table 4

VII. Conclusions

A host of recent research, both theoretical and empirical, has emphasized the importance of individuals' subjective survival forecasts for predicting mortality and behavior. Most prominently, Perozek (2008) suggests that SSFs perform better than population life tables in predicting age- and gender-specific mortality rates. Using data from the Health and Retirement Study (HRS), we present a contrarian view. HRS respondents below age 65 are pessimistic about their short-term survival prospects, and this pessimism has grown over time – in spite of steady increases in survival and longevity, subjective forecasts of survival to age 75 did not increase from 1992 to 2006. More importantly, SSFs predict in-sample survival rates poorly compared to population life tables.

The poor performance of subjective forecasts in explaining in-sample survival stems largely from "flatness bias", the tendency for individuals to understate the likelihood of living to relatively young ages while overstating the likelihood of living to ages beyond 80. In the HRS, flatness bias is sufficiently strong that it suggests that most individuals, at a given point in time, do not recognize that mortality risk increases with age.

In order to investigate the mechanisms underlying the poor performance of the SSFs, we develop and estimate a latent-factor model of the process by which individuals form subjective forecasts. Individuals' beliefs about their peers' survival prospects, as measured in a supplemental module in the 2006 HRS, are crucial for the identification of this model's parameters. The resulting estimates suggest that the SSFs incorporate several sources of error

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to recover cov(Y_i, d_i) / var(d_i), which is the coefficient on SSF_i in this regression if SSFs included no errors (ignoring that the models underlying Table 2 are probits rather than linear regressions). Specifically, cov(Y_i, d_i) / var(d_i) = [cov(Y_i, $g_i + d_i + e_i$) / var($g_i + d_i + e_i$)] × [var($g_i + d_i + e_i$)/ var(d_i)]. Because var($g_i + d_i + e_i$) / var(d_i) = var($SSF_i - A_i$) / var(d_i) = 0.3448, the estimated effects of SSF_i in Table 2 would roughly triple in magnitude if var(g_i) = var(e_i) = 0. We thank an anonymous referee for suggesting these ideas and bias corrections.

that, in combination, overwhelm the useful information they convey. Specifically, relative to actuarial survival forecasts, roughly two-thirds of the excess variation in the SSFs represents errors in guessing survival probabilities and response noise, rather than genuine information about an individual's health and survival prospects.

In spite of our largely negative conclusions, we envision an important role for additional research on SSFs. Future work will likely focus on improvements in data collection techniques intended to increase the reliability of these measures. The HRS questions designed to elicit cohort survival forecasts represent innovative examples of such techniques. Future research will also investigate why SSFs predict group-level mortality so poorly. The payoff of such an investigation is potentially large – published life tables have systematically underpredicted the longevity of successive cohorts for more than a century, so subjective forecasts have the potential to greatly improve the accuracy of longevity projections. Although our results suggest that this potential is largely unfulfilled in the HRS, researchers will continue to analyze SSFs because accurate longevity forecasts are crucially important for the optimal design of policies such as Social Security, Medicare, and Medicaid.

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Table 1: Average Subjective and Life Table-Based Forecasts of Survival to Ages 75 and 85, by HRS Wave and Gender

Panel A: Age 75

	Men			*Women*		
Wave	Subjective	Life Table	N	Subjective	Life Table	N
1992	62.53	61.30	5268	65.80	74.45	6490
1994	62.50	61.96	3990	64.11	74.57	5678
1996	63.93	62.88	3461	66.46	74.83	5367
1998	62.79	64.27	3691	67.15	75.29	5726
2000	63.08	65.46	3142	67.34	75.61	5089
2002	61.80	66.74	2520	67.69	76.42	4335
2004	61.33	67.20	3384	66.21	76.78	5340
2006	59.10	67.56	2416	65.29	77.20	4026

Panel B: Age 85

	Men			*Women*		
Wave	Subjective	Life Table	N	Subjective	Life Table	N
1992	39.58	26.99	5267	45.92	44.23	5313
1994	38.96	27.42	4411	43.08	44.29	4997
1996	41.57	28.45	4129	46.56	44.56	4900
1998	39.16	29.64	3655	46.13	44.58	5018
2006	39.30	32.74	2377	45.95	47.02	3959

Notes:

1) All forecasts are converted to a 0-100 scale, with 0 meaning "no chance" and 100 meaning "absolutely certain".

2) Observations in all years after 1992 are weighted in order to match the 1992 age distribution of respondents within each gender.

Table 2: The Predictive Power of Subjective and Life Table-Based Survival Forecasts for in-Sample Survival in the HRS

	Sample Includes Those Eligible to Reach Target Ages		*Sample Includes All Initial-Year Respondents*	
	(1)	(2)	(3)	(4)
Subjective Forecasts	0.144	0.128	0.156	0.133
	(0.038)	(0.038)	(0.010)	(0.010)
Life Table-Based Forecasts	1.055	1.052	1.033	0.981
	(0.060)	(0.067)	(0.017)	(0.019)
Additional Controls?	No	Yes	No	Yes
Pseudo-R^2	0.253	0.279	0.306	0.322
Sample size	1,180	1,180	14,133	14,133

Notes:

1) The entries in each column are marginal effects from probit models of within-sample survival in the HRS as a function of subjective and life table-based survival forecasts.

2) Columns (2) and (4) include additional controls for marital status, race, ethnicity, living arrangements, assets, income, education, and body mass index.

3) Standard errors, given in parentheses, are robust to arbitrary heteroskedasticity.

Table 3: Regression Estimates of the Relationship Between log(P_{85}) and log(P_{75}) for Selected Ages of HRS Respondents

		Subjective Forecasts		Implied by Constant Hazard Rate	Based on Life Tables
		OLS	Rescaled OLS		OLS
Age	N	(1)	(2)	(3)	(4)
50	908	1.17	1.64	1.40	2.33
		(0.09)	(0.14)		(0.01)
55	2359	1.18	1.65	1.50	2.43
		(0.08)	(0.11)		(0.01)
60	2300	1.17	1.64	1.67	2.62
		(0.08)	(0.10)		(0.01)
61	2109	1.15	1.61	1.71	2.68
		(0.08)	(0.11)		(0.01)
62	1783	1.08	1.51	1.77	2.73
		(0.08)	(0.12)		(0.01)
63	1573	1.17	1.64	1.83	2.82
		(0.08)	(0.11)		(0.01)
64	1277	1.10	1.54	1.91	2.91
		(0.08)	(0.12)		(0.01)
65	728	1.12	1.56	2.00	3.03
		(0.09)	(0.15)		(0.01)

Notes:

1) The entries in each column are the age-specific coefficients and associated standard errors (in parentheses) from linear regressions of log(P_{85}) on log(P_{75}) interacted with an exhaustive set of indicator variables for an individual's age, as given in equation (5) in the text. For example, the entries in the top row are estimates of β_{50} from equation (5).

2) The "Rescaled OLS" models in column (2) are estimated by two-sample instrumental variables (TSIV), as described in the text.

3) Standard errors are robust to clustering at the respondent level and to arbitrary heteroskedasticity.

Table 4: Estimates of a Latent Factor Model of Subjective Survival Forecasts, Cohort Forecasts, and Revised Forecasts

Observed Second Moments		*Estimated Parameters*	
var(SSF_i)	836.66	λ_d	16.68 (0.85)
var($CSSF_i$)	458.84	λ_g	7.06 (0.94)
var($RSSF_i$)	530.84	var(e_i)	361.10 (31.70)
cov(SSF_i, $CSSF_i$)	184.61	var(v_i)	379.23 (23.28)
cov(SSF_i, $RSSF_i$)	423.47	var(u_i)	222.92 (28.31)
cov($CSSF_i$, $RSSF_i$)	173.31	var(d_i)	278.21 (28.15)
		var(g_i)	49.86 (30.21)

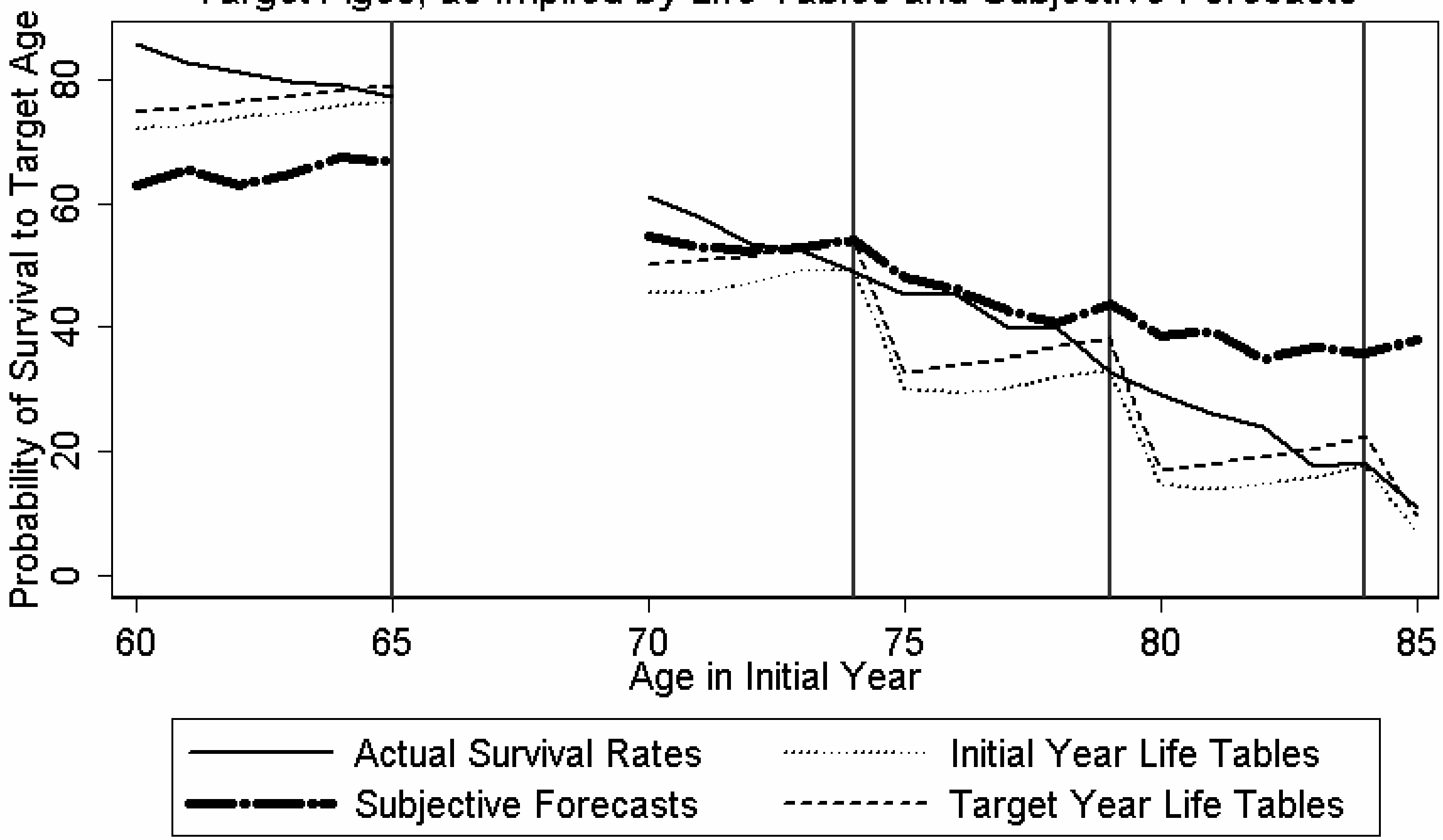
Notes:
1) The estimation sample includes all 2006 HRS respondents who provided valid responses to special module questions about cohort subjective survival forecasts and revised subjective survival forecasts. N = 1348.

2) We compute standard errors (in parentheses) for all estimated quantities using a bootstrap procedure with 500 replications.

3) See Section V of the text for more details on the latent factor model described by equations (9)-(11).

Figure 1

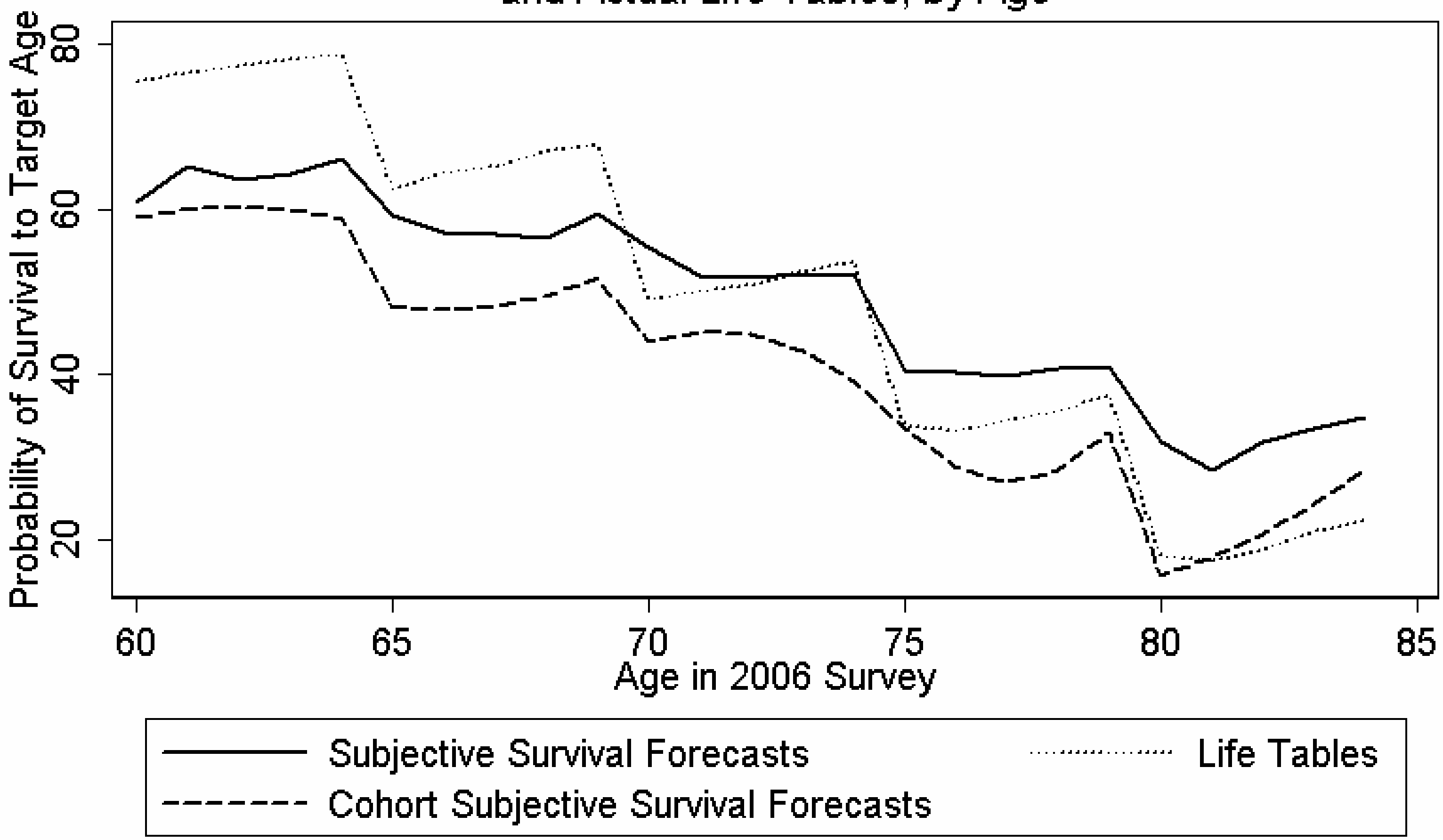
In-Sample Survival Rates and Probabilities of Survival to Target Ages, as Implied by Life Tables and Subjective Forecasts



Notes: "Target ages" for subjective and life-table forecasts refer to the age to which respondents report their subjective probability of surviving; these target ages equal 75 for respondents age 65 and younger, 85 for those age 70-74, 90 for those age 75-79, 95 for those age 80-84, and 100 for those age 85. The initial waves of the HRS/AHEAD did not include primary respondents older than 65 and younger than 70, resulting in the “gap” in all four series between those ages. See Section III of the text for more details.

Figure 2

Subjective Survival Forecasts, Cohort Survival Forecasts, and Actual Life Tables, by Age



Notes: The estimation sample includes all 2006 HRS respondents who provided valid responses to special module questions about cohort subjective survival forecasts and revised subjective survival forecasts. N = 1348.

Appendix Table 1: Average Subjective and Life Table-Based Forecasts of Survival to Ages 75 and 85, by HRS Wave and Gender - UNWEIGHTED

Panel A: Age 75

	Men			*Women*		
Wave	Subjective	Life Table	N	Subjective	Life Table	N
1992	62.53	61.30	5268	65.80	74.45	6490
1994	62.66	62.89	3990	64.22	75.16	5678
1996	64.07	64.98	3461	65.89	76.29	5367
1998	63.06	65.44	3691	66.77	76.44	5726
2000	63.75	65.97	3142	67.01	76.75	5089
2002	62.06	67.03	2520	67.35	77.18	4335
2004	61.35	67.67	3384	67.96	77.53	5340
2006	63.88	68.03	2416	68.96	77.90	4026

Panel B: Age 85

	Men			*Women*		
Wave	Subjective	Life Table	N	Subjective	Life Table	N
1992	39.58	26.99	5267	45.92	44.23	5313
1994	38.93	27.82	4411	43.15	46.56	4997
1996	41.30	29.39	4129	46.52	45.07	4900
1998	39.24	30.16	3655	46.18	45.21	5018
2006	39.78	33.18	2377	48.55	47.43	3959

Notes:

All forecasts are converted to a 0-100 scale, with 0 meaning "no chance" and 100 meaning "absolutely certain".

Appendix Table 2: Age-Specific 10- and 11-Year Survival Probabilities and Predicted Survival Probabilities from Subjective Forecasts, Initial Year Life Tables, and Target Year Life Tables

		Predicted Survival Probabilities Based on:			
Age in Initial Year	*Actual Survival Probability*	*Initial Year Life Tables*	*Target Year Life Tables*	*Subjective Forecasts*	*Target Age*
60	85.806	71.137	75.666	62.976	75
61	82.807	71.520	76.087	65.545	75
62	81.170	73.179	77.146	63.018	75
63	79.827	73.900	77.921	64.756	75
64	79.296	75.091	78.859	67.496	75
65	**77.476**	**75.752**	**79.502**	**66.789**	**75**
70	61.093	45.590	50.140	54.712	85
71	57.923	45.687	50.796	53.098	85
72	53.504	47.219	51.486	52.427	85
73	52.194	49.321	53.223	52.961	85
74	**49.596**	**49.408**	**54.462**	**54.094**	**85**
75	45.455	30.078	32.713	48.060	90
76	45.289	29.454	33.962	46.310	90
77	40.096	30.095	34.971	42.724	90
78	39.691	32.131	36.941	40.707	90
79	**32.939**	**33.060**	**38.284**	**43.873**	**90**
80	29.244	14.621	17.018	38.740	95
81	25.988	13.751	17.967	39.250	95
82	24.013	14.766	19.169	34.852	95
83	17.469	15.696	20.341	36.801	95
84	**18.029**	**17.587**	**22.345**	**35.960**	**95**
85	10.817	6.918	9.512	37.930	100

Note: For ages 60-65, the initial year refers to 1996 and the target year refers to 2006. For ages 70-85, the initial year refers to 1993 and the target year refers to 2004. Rows in **bold** are initial ages for which living respondents reach their target age in the target year. For example, sample members aged 65 in 1996 were asked about the probability of living to age 75, i.e., of living to the year 2006. All probabilities are converted to a 0-100 scale, with 0 meaning "no chance" and 100 meaning "absolutely certain".