# YOLO: Mortality Beliefs and Household Finance Puzzles

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**Abstract**

*Subjective* mortality beliefs affect pre- and post-retirement consumption and savings decisions, as well as portfolio allocation. Our new survey evidence shows that younger individuals overestimate their mortality at short horizons while older individuals overestimate their long-run chances of survival. The formation of these beliefs across age cohorts can be attributed to overweighting the most salient causes-of-death, which change over the life-cycle. This bias matters empirically: Survival expectations correlate with heterogeneity in savings rates and investment experience. These beliefs make the young (old) more impatient (patient), and when embedded in a conventional dynamic life-cycle model with pre-cautionary savings, they cause the young to under-save (they have 10% less saved upon retirement) and retirees to not fully draw down their assets (they consume 12% less during retirement). In addition, we propose a few mechanisms through which mortality beliefs could affect the equity premium, particularly through a reduction in the risk free rate.

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Individuals often have distorted views of low probability events and few events in life happen less frequently than death. Yet visions of our own mortality can have important economic consequences. For example, sharks are responsible for an average of just one U.S. death per year (cows kill around 20 people on average), but according to a headline in the August 29, 2015 edition of the L.A. Times, “La Jolla beach closed after shark sighting.” Meanwhile, in a survey conducted by Prudential Financial, Inc., the results of which were presented in a commercial aired during Super Bowl 47, 400 people were asked to list the age of the oldest person they know. The average answer exceeded 90 years old. Clearly, this means that we are living longer and that you should contact Prudential today.

Motivated by recent efforts to use survey elicited beliefs to understand discrepancies between classical economic models and real outcomes,[1] we measure subjective mortality beliefs and consider their consequences across multiple economic fields that are connected by a common foundation - the inter-temporal nature of household decision-making. We find that these elicited beliefs jointly bring us closer to understanding why some young people undersave towards retirement (Skinner (2007)), retirees do not fully draw down their assets (Poterba et al. (2011)), and the required equity-premium has historically been high (Mehra and Prescott (1985)). The reason we study this mechanism is that subjective life-expectancies have direct bearing on what is among the equations most studied by the discipline: the intertemporal trade-off between consumption today and the discounted present value of future consumption streams,

$$V_t^*(\cdot) = \max_{C_t}\{u(C_t) + \beta \mathbf{E_t}[s_{t+1}V_{t+1}^*(\cdot)]\}.$$

The discount factor ($\beta$) and the utility function’s curvature ($\rho$) have been studied countless times. However, despite no indication that subjective mortality beliefs ($\mathrm{E}[s]$) are any less meaningful, they have received much less attention by the literature. The dearth of research is all the more

[1]These efforts have been applied to the recent housing boom (Soo (2015) and Bricker et al. (2015)), historical asset prices (Greenwood and Shleifer (2014)), or the difficulty implementing monetary policy (Coibion et al. (2015)).

striking considering that practitioners widely use these beliefs to advertise financial products and to develop long-run financial plans (e.g. Figure 1).

Using a new, professionally collected survey of nearly 5,000 respondents that builds a comprehensive picture of survival beliefs over the entire life-cycle, we find that the subjective life-expectancy (SLE) distribution is heavy-tailed in comparison to actuarial tables provided by the Social Security Administration (SSA). That is, young individuals believe their chances of survival beyond the next few years are lower than that predicted by actuarial data (as much as 7 ppt under-estimation), while respondents beyond the age of retirement believe there is a reasonable chance of surviving to extreme old age (as much as 10 ppt overestimation of surviving at least an additional ten years).

In order to better understand that these survey beliefs are meaningful and not caused by other unobserved factors, we diagnose the source of these expectation errors.[2] We find that distorted mortality beliefs correspond to salient, cohort-specific stereotypes of cause-of-death (Bordalo et al. (2012) and Bordalo et al. (2014)). Young people associate death with near-term rare events (e.g. plane crashes), the probability of which they overweight. As people age, these rare events take a cognitive backseat to thoughts of health and the normal course of aging. Since the average person who survives to old age has comparatively better health than cohort members to have previously died, long-term survival is perceived to be more likely than it is on average.

These errors in subjective survival beliefs matter for key aspects of financial decision-making. Using off-the-shelf questions from commonly cited household surveys (e.g. the Survey of Consumer Finances), large subjective survival belief errors are associated with a greater propensity to not save or even an over-reliance on credit cards on a month-to-month basis. Similarly, increased (decreased) expectation errors are associated with an increase (decrease) in the perceived likelihood of using one's savings more quickly, even after accounting for the respondent's age. These

[2] It would be unethical to experimentally alter subjects' mortality beliefs, so our approach is akin to understanding the chemistry linking illnesses to environmental factors, such as the body of evidence connecting smoking to higher rates of cancer.

same expectation errors are associated with a decreased tendency to describe oneself as having investment experience. Our findings hold even after accounting for income, demographic, and educational differences, as well as after providing a random sample of respondents with information on survival rates from actuarial tables. Using a comparison to the effect of respondents' financial literacy on savings behavior to gauge the economic significance, the magnitude of the relation between survival beliefs and savings rates is at least as large.

We embed these subjective beliefs into the simplest form of a dynamic life-cycle model with pre-cautionary savings, the solution to which furthers our understanding of seemingly disconnected empirical regularities. First, some argue that there is under-saving for retirement that can not fully be explained by income heterogeneity (Skinner (2007)). Our elicited subjective beliefs suggest that individuals are too pessimistic about short-term survival rates, causing them to undersave by about 10 percent relative to our benchmark model calibrated to actuarial data. Second, a distinct body of research finds that retirees do not fully draw down their assets, even after accounting for different bequest motives (Poterba et al. (2011)). Owing to retirees' overestimation of long-term survival rates, individuals consume 12 percent less during retirement. This mechanism is independent from any income differences that may exist upon reaching retirement.

A related challenge for models of consumption and savings decisions is for the underlying framework to jointly describe the behavior of asset prices.[3] We use two simple approaches to show that the introduction of our survey-based, subjective mortality beliefs contribute to our understanding of the high levels of the historical equity premium (Mehra and Prescott (1985)). First, we use GMM to estimate the return on the risky-asset required to achieve certainty-equivalent levels of wealth-accumulation under our benchmark calibration with actuarial survival rates. The return premium has to increase by as much as a factor of three, even with reasonable levels of risk tolerance, as low as two. To understand this result in this partial equilibrium setting, younger in-

[3] A few pieces of literature notice the disconnect between models of lifetime consumption and savings, and asset prices. For example, Addoum et al. (2014).

dividuals (who tilt their portfolios towards equity to hedge against future income risk) need higher returns to get them to delay consumption during this crucial period of wealth accumulation. Second, we solve an overlapping generations model (OLG) model that is in the spirit of Constantinides et al. (2002) to describe the effect of mortality beliefs on the risk free rate. The model relies on the relative attractiveness of debt and equity at different phases of the lifecycle combined with the saving motives of the young relative to those nearing retirement. As in Constantinides et al. (2002), the young prefer equity because it hedges against future income uncertainty, while the old – who consume out of their savings during retirement – prefer less volatile bonds. The attractiveness of bonds to those nearing retirement lowers the rate of return, an effect deepened by retirees' high savings rates caused by optimistic survival beliefs. If the young had reasonable survival beliefs, they would enjoy this opportunity to sell bonds to the old and then purchase equity to hedge against uncertain future incomes, which would lower the equity premium. Instead, the young increase their consumption because their survival beliefs make them impatient. This allows the risk free rate to stay low.

This paper's primary contribution is to expand the predictive power of the canonical life-cycle framework – including the domain of asset prices – simply by feeding it new data on subjective survival beliefs. There have been a number of excellent efforts to explain empirical regularities in the literature on consumption and savings decisions. For instance, they employ precautionary savings as a mechanism (Gourinchas and Parker (2002) and Lusardi (1998)), self-control problems (O'Donoghue and Rabin (1999)), and hyperbolic discounting (Laibson (1997)). However, "there is little sharp evidence" that these preferences affect household balance sheets (Zinman (2014)). To better understand why many retirees do not consume all of their assets, some have studied bequest motives (Bernheim et al. (1985) and Hurd (1989)), as well as their interaction with wealth inequality (Nardi and Yang (2015)) and health (Lockwood (2014)). The advantage of our approach, relative to this literature, is that our findings can reconcile what appears to be contradictory behavior at opposite ends of the life-cycle.

Our paper also segues with research on probability weighting. It is well-documented that individuals place too much weight on low-likelihood events, a literature which began in part because of Lichtenstein et al. (1979)'s findings that people overestimate the frequency of rare causes of death. Probability weighting has been applied to seminal theories such as Cumulative Prospect Theory (Tversky and Kahneman (1992)), which in turn has been shown to have important consequences for asset prices (Barberis and Huang (2008)) and portfolio choice (Polkovnichenko (2005)). Related to these studies is a literature on tail events and their contribution to personal investing, but only recently have scholars considered the ex ante beliefs of these rare events (Goetzmann et al. (2016) and Gao and Song (2015)). Perhaps the most striking market-based evidence that probability overweighting contributes to biased survival beliefs, and that these beliefs meaningfully affect economic decisions, comes from research showing that many individuals purchase too much insurance against unlikely events (Sydnor (2010) and Bhargava et al. (2015)).

Finally, we contribute to an emergent literature on the measurement and implications of subjective expectations (Christelis et al. (2015)), with a particular interest in mortality beliefs (Hamermesh (1985)). Empirical studies confirm the role of subjective mortality beliefs among the retired using the Health and Retirement Survey (Bisetti (2015)) or study annuitization (Inkmann et al. (2011)). Puri and Robinson (2007) and Post and Hanewald (2013) use other household surveys to provide initial evidence of the connection between life expectancy beliefs and economic decision-making. Our paper also complements a literature, which interprets evidence of subjective mortality beliefs through the lens of life-cycle models. Some consider increased longevity risk (Cocco and Gomes (2012)), survival ambiguity (Groneck et al. (2013)), while other studies are focused on respondents older than 50 or even the oldest old (Gan et al. (2005) and Wu et al. (2014)). The latter calibrations therefore do not fully account for the younger years of life, a crucial period for asset accumulation. Another distinguishing feature relative to this literature is that our paper considers the cognitive factors that lead to these distorted mortality beliefs. Doing so helps us develop a unified understanding – the salience of cause-of-death – as to why errors in subjective life-expectancies differ across survival horizons and over the life-cycle.

This paper is organized as follows. Section 1 provides survey evidence on subjective life-expectancies, while Section 2 demonstrates their connection to household financial behavior. Section 3 describes our life-cycle model. Section 4 presents the solution to the model and describes its findings on consumption, savings, and investment over the life-cycle. Concluding thoughts are provided in Section 5.

# 1 Survey Evidence on Subjective Life Expectancies

## 1.1 Survey Description and Sample Characteristics

We contracted Qualtrics Panels to provide us with a survey of 5000 respondents, screened according to national residency and age. All respondents were required to be U.S. residents and have English be their primary language. Respondents were drawn from the following six ages, 28, 38, 48, 58, 68, and 78, with the distribution roughly matching the relative proportion of the population at each age. The survey specifically targets these ages to avoid respondents who are about to or who have recently reached milestone ages, such as 40-years-old. We further requested an even gender distribution sample-wide. The survey administers also included additional filters eliminating respondents who write-in gibberish for at least one response or who complete the survey in less (more) than five (thirty) minutes.

The survey collects demographic information on the respondents (Table 1). The typical survey respondent looks similar to those in the median U.S. household. A little over half are female, 68 percent have children, and just over half are married. Similar to U.S. population statistics, 29 percent have a bachelor's degree and around 13 percent have an advanced degree, although the fraction of respondents without high school degrees appears underrepresented. Furthermore, the income distribution is reasonable, with the largest group of respondents having between 50,000 and 100,000 dollars in household income.

Table 2 presents summary statistics on other variables of interest. The survey starts by asking respondents to indicate their survival likelihood beliefs. Respondents are asked the likelihood that they live at least an additional $y = \{1,2,5,10\}$ years. We randomly assigned respondents to one of these four survival horizons, while one-fifth of respondents were asked all four horizons sequentially. To elicit survival beliefs, the survey uses a slider tool ranging from zero to one hundred (see the survey Appendix), which respondents control with their mouse. The use of the slider helps respondents visualize a probability distribution. This visualization is well-known to produce more accurate surveyed probability assessments (e.g. Treiblmaier and Filzmoser (2011)) by alleviating the use of heuristics or mental shortcuts to assign numerical probabilities (for example, the use of 90 as a substitute for any number close to one hundred).

To provide a comparison to more widely-used surveys, respondents are asked on a separate page to indicate their expected longevity (the age to which they will survive), a question also included in the Survey of Consumer Finances (SCF). The survey randomizes the order in which survival beliefs and longevity beliefs are asked in order to mitigate the influence of one question on the other. On the same pages of the survey, respondents are asked to indicate their degree of confidence in their answers on survival likelihood and expected longevity. Doing so primes respondents to carefully consider their answers about mortality beliefs. The survey's main questions on mortality beliefs ask about the chances of survival, rather than the chances of dying, because the latter could inflate beliefs about the likelihood of death (Payne et al. (2013)).

Following the elicitation of mortality beliefs, the survey gauges the cognitive factors that respondents use to formulate their beliefs, as well as their personal assessment of the frequency of rare deaths. First, we ask respondents to indicate the weight they place on certain causes-of-death when assessing their own chances of survival. The causes-of-death can roughly be categorized as relating either to natural causes, such as aging and health related, or unnatural events, such as car and plane crashes. We also ask respondents to estimate the number of annual deaths by plane crash and the number of people struck by lightning.

The survey elicits savings rates in a few different ways, by asking about the share of income saved, when respondents plan to use their savings, and alternatively, the respondent's investing experience. The set of potential responses to these questions are divided into broad categories to lessen the scope for recall bias. For example, the survey asks for the approximate share of monthly income saved (e.g., "I save around 10% of my monthly income"). The remainder of the survey is designed to resemble more commonly referenced household surveys such as the SCF or the Health and Retirement Survey. The remaining questions guage risk tolerance, income expectations, and personal health assessments. The survey also includes off-the-shelf questions on financial and numerical literacy (Lusardi and Mitchell (2011) and Cokely et al. (2012)).

## 1.2 Survival Beliefs Over the Life cycle

Figure 2 plots average subjective survival beliefs by current age and survival horizon separately for males and females. The figure uses a fractional polynomial fit to smooth through respondents' 1, 2, 5, and 10-year ahead survival forecasts across the complete set of 28, 38, 48, 58, 68, and 78 year-olds. These fitted estimates give a sense of how short-term survival beliefs change over the life-cycle. Ninety-five percent confidence intervals also accompany these estimates, but owing to the large sample size, the point estimates are considerably precise.

Survival beliefs change over the life-cycle. On average, younger (older) individuals underestimate (overestimate) their survival chances relative to actuarial statistics from the Social Security administration. For example, the average male respondent who is 38 years old makes more than a ten percentage point underestimation of surviving an additional year. Only when male respondents turn 68 years old are their subjective survival beliefs equal to the actuarial statistics, although their

10-year ahead forecast are overly optimistic by about five percentage points. The results are similar for females.

There are many reasons to be confident that the flip from under- to over-estimation of survival likelihood as the average respondent gets older is a robust phenomena. First, we find similar results for respondents' beliefs about their own longevity (Figure 3). Both men and women underestimate their expected longevity when they are currently 58-years-old or younger. For example, a 28-year-old female is projected to live to 86-years-old, but the average 28-year-old female respondent expects she will live to be 84. For both genders, 68-year-olds are better calibrated to their expected longevity, while 78-year-olds overestimate how old they will live. Hence, there is an upward trend in subjective longevity beliefs over the life-cycle, thereby corroborating our results on survival beliefs. These findings address any lingering concerns that the survival belief results are caused by omitted factors that would make respondents have difficulty expressing their beliefs via probabilities.

A second reason to have confidence that personal survival beliefs change over the life-cycle is the finding's robustness across demographic characteristics and to different experimental treatments (Appendix, Table A.1). Among our more convincing tests, we gave half of all respondents precise information on the actuarial likelihood of survival and expected longevity for a male or female around their age. There are no strong differences in subjective mortality beliefs between respondents who did and did not receive this information. Additionally, the quadratic shape of these survival belief errors over the life-cycle holds after accounting for resdondent's numerical literacy and treatments for asking about all four survival horizons, as well as cigarette smoking and personal health assessments.

Yet another reason to have confidence in the result is that previous literature has hinted at life-cycle survival belief changes across a variety of settings and sample populations, even though few data sets provide as comprehensive a look at survival beliefs over the life-cycle. An argument could be made that our online survey is not of the same quality as the interview surveys frequently employed throughout the household finance literature. However, a similar inflection in survival belief errors across ages is found in the University of Michigan's Health and Retirement Survey (Groneck et al. (2013)). Another possibility is that the average person has difficulty working with probabilities. To counter this argument, Jarnebrant and Myrseth (2013) survey engineering grad students and find that they underestimate their survival at short horizons and overestimate it at long horizons. Furthermore, our results could be unique to U.S. respondents, but the findings are similar in other countries (Wu et al. (2014)).

Lastly, our analysis describes the mechanisms that lead to distorted survival beliefs. Because it would be unethical to experimentally manipulate respondent's survival beliefs, we seek to diagnose the source of these beliefs and develop a unified understanding of survival beliefs over the life-cycle. Evidence of such a mechanism is described in the following section and it furthers our confidence that the empirical findings are meaningful.

## 1.3 How do Mortality Beliefs Form?

There is much evidence that mortality beliefs change systematically over the life-cycle, but to the best of our knowledge, no research has sought to understand how these distorted belief form. We argue that when individuals think about death, they use an availability heuristic and follow certain stereotypes about the cause-of-death at different ages over the life-cycle. Young people are thought to die because of unintended injury or other unnatural causes. Unnatural causes-of-death are thought to occur more often than they do, because individuals overweight salient unlikely events. Meanwhile, failing health causes death among the elderly. Older respondents are optimistic about their long-term survival, because the average respondent is of comparatively better health than other members of their cohort to have perished. Because natural deaths are less imaginable than deaths caused by rare events, the likelihood of occurrence is under-weighted.

We provide evidence that rare events play a disproportionate role in the formation of survival beliefs. Table 3, Panel A presents summary statistics on the weights respondents place on different causes-of-death on a scale from one to one hundred. Respondents place roughly half as much weight on unnatural causes, such as physical violence, as they do medical conditions or the normal course of aging. According to statistics from the Centers for Disease Control and Prevention, unnatural causes account for roughly just a twentieth of all deaths.

To test how different individual attributes contribute to these risk factors, Table 3, Panel B presents estimates of the following regression model:

$$risk.factor.weight_i = \beta_0 + \beta_1 \cdot survival.optimism_i + \sum_{l=0}^{5} \beta_{2l} \cdot age.category_i + \Gamma \cdot X_i + \varepsilon_i. \quad (1)$$

The dependent variable, $risk.factor.weight$, is equal to the weight respondent $i$ places on the corresponding risk factor divided by the sum of the weights $i$ places on all nine risk factors. The independent variable, $survival.optimism$, equals $E_{it}\left[surv(t+l)\right] - Pr_{it}\left[surv(t+l)\right]$, where $t$ is respondent $i$'s age and $l = \{1, 2, 5, 10\}$, and survival probabilities are from the SSA. We normalize $survival.optimism$ so that a one unit increase equals a standard deviation increase. The regression uses a set of indicator variables for the respondent's age, $age.category = \{38, 48, 58, 68, 78\}$, while setting 28-years-old as the omitted category. The matrix $X$ includes other control variables such as gender and the assignment to different experimental treatments. Standard errors are clustered to allow for correlated residuals across ages.

The relative weighting on these different risk factors correlates with differences in survival beliefs. The coefficient on $survival.optimism$ is positive and statistically significant for natural aging ($coef = 3.46$, $s.e. = 0.10$) and diet ($coef = 1.11$, $s.e. = 0.18$), while it is not statistically different from zero when the dependent variable is the weight on medical factors. Meanwhile, the coefficient estimate is negative and statistically significant for all six of the unnatural causes-of-death, with the estimate ranging from -0.30 to -0.93. To provide one example to convey the economic significance of these results (column 9), the average weight share on freak events is roughly 7 and a one standard deviation increase in survival optimism reduces the weight to 6, roughly a 13 percent decrease.

Likewise, respondent age plays a prominent and distinct role in determining the relative weighting. The relative weight placed on natural, medical, and lifestyle causes-of-death is monotonically increasing in respondent age. For example, the share of the weight on the natural course of aging increases by 4.8 (or 20 percent of the average share) when comparing 78-year-olds to 28-year-olds. Similarly, the share of the weight on all six of the unnatural causes-of-death decreases monotonically in respondent age. Taken together, these findings suggest that not only do mortality beliefs change over the life-cycle, but how respondents think about death does as well.

Several additional results in Table 3, Panel B give us confidence that we correctly assess personalized subjective beliefs about different causes-of-death. First, the differences in risk factor weighting across genders corresponds to well-known differences between men and women. On average, men in our survey place less weight on diet (column 3, $coef = -0.75$, $s.e. = 0.16$) and medical conditions (column 2, $coef = -0.42$, $s.e. = 0.40$), a result that accords with findings in the medical profession that men are 20 percent more likely than women to dismiss results from medical screenings on cholesterol and heart health (Agency for Healthcare Research and Quality). Men place a greater weight on risky lifestyles (column 8, $coef = 1.10$, $s.e. = 0.17$). On the other hand, they place less weight on traffic accidents (column 4, $coef = -0.59$, $s.e. = 0.17$), consistent with men having lower subjective assessments of the risks of driving and paying higher car insurance premiums as a result.

Secondly, the relative weight placed on natural disasters corresponds to the actual likelihood of experiencing a disaster, furthering our confidence in the survey results. We include as an independent variable the logarithm of one plus the number of natural disaster deaths in the respondent's zip code. The number of deaths by natural disaster is taken from the Spatial Hazard Events and

Losses Database (SHELDUS) and is the sum over the years 2001 to 2010.[4] The regression estimate implies that a one percent increase in the number of deaths by natural disaster in the area is associated with 0.93 ($s.e. = 0.18$) more weight placed on natural disasters when respondents develop their mortality beliefs (column 6). Comfortingly, the number of natural disaster deaths in the respondent's vicinity does not predict any of the other eight risk factors.

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We provide additional evidence that imaginability or salience play a critical role in developing subjective survival beliefs. Specifically, we test the relation between own subjective survival beliefs and respondent estimates of the number of people to die annually either in plane crashes or by lightning strike. While roughly an equal number of people fall victim to these two unnatural deaths, plane crashes are presumably more easily visualized and awareness of the event is even reinforced through media coverage.

To test the relation between survival beliefs and imaginability, Table 4 presents estimates of the following Poisson regression model:

$$log\left(\mathrm{E}\left(\#deaths|X_i\right)\right) = \beta_0 + \beta_1 \cdot survival.optimism_i + \sum_{l=0}^{5} \beta_{2l} \cdot age.category_i + \Gamma \cdot X_i + \varepsilon_i.$$

The dependent variable equals respondents' beliefs about either the number of Americans to die in plane crashes (columns 1 and 2) or the number struck by lightning (columns 3 and 4).[5] We use a Poisson regression because the dependent variable is truncated at zero. We calculate robust standard errors that allow for correlated residuals by respondent age.

In support of our hypothesis, survival optimism is negatively correlated with beliefs about the number of people to die in plane crashes, but does not relate to lightning strikes. In columns 1 and

[4]The SHELDUS data is provided at the county level. We map counties to zip codes using the 2010 concordance from the Missouri Census Data Center.

[5]The right tail of these variables are Winsorized at 2.5 percent.

2, the coefficient estimate on *survival.optimism* is about equal to -0.093 and is statistically significant at the one percent level. This implies that a one standard deviation increase in subjective survival likelihood is associated with a difference in the logs of expected counts of number of deaths that decreases by about nine percent. On the other hand, the relation between *survival.optimism* and subjective assessments of the number of people struck by lightning is not statistically different from zero (columns 3 and 4).

## 2 Do Mortality Beliefs Affect Household Finances?

Before studying the aggregate implications of subjective mortality beliefs, we provide evidence that these beliefs correlate with household balance sheets in ways that are consistent with life-cycle theory. Our evidence comes from estimates of the following ordered logit model:

$$y^* = \beta_{1k} \cdot survival.optimism_i + \Gamma \cdot X_i + \varepsilon_i \tag{2}$$

where $y^*$ is the unobserved dependent variable and we observe the response

$$y = \begin{cases} 0 & if\ y^* \leq \mu_1 \\ 1 & if\ \mu_1 < y^* \leq \mu_2 \\ \vdots & \\ k & if\ \mu_k < y^* \end{cases}$$

over $k$ categories. The coefficient $\beta_{1k}$ captures the ordered log-odds estimate of moving up a category of $y$ for a one standard deviation increase in *survival.optimism*. We estimate this model for three different dependent variables, each of which gives us a sense of personal savings rates. The first measure is the fraction of monthly income saved ranging from needing to rely on credit cards to at least 50 percent of income. The second measures asks when respondents plan to use their savings. To add further robustness, because respondents may experience different income shocks at difference times thereby adding noise to individual estimates of savings rates, we measure respondents revealed *intent* to save by asking about their experience investing. The relationship between mortality beliefs and savings is potentially sensitive to other life-cycle and demographic factors, so the matrix $X_i$ controls for many relevant personal characteristics including age, income, education, and marital status, as well as personal preferences and abilities such as risk-tolerance and numerical literacy. We estimate the model with robust standard errors clustered by respondent age.

Table 5 presents estimates of equation 2. Column 1 estimates the effect of survival optimism on savings rates while including a large set of control variables. To offer a comparison to another important determinate of personal finances, Column 2 adds to the right-hand side an indicator variable for the respondent's financial literacy. The regression in Column 3 adds the respondent's income and education in order to give a sense of how much of the relationship between survival beliefs and savings is brought about by differences in economic circumstances. Columns 4 through 6 are analogous to 1 through 3, except the independent variable of interest is $longevity.optimism$, the difference between the respondent's subjective longevity beliefs and expected lifespan according to the SSA. These regressions suggest robustness to different ways of measuring subjective beliefs.

Across all measures, greater survival optimism correlates with higher savings rates. The regressions in Panel A use the share of monthly income saved as a dependent variable. In column 1, the coefficient on $survival.optimism$ equals 0.19 and is statistically significant at the one percent level. The coefficient estimate implies that a one standard deviation increase in survival optimism is associated with a 19 percent increase in the ordered log-odds of moving to a higher savings category. In column 2, the coefficient estimate on $survival.optimism$ is not much changed and the coefficient on the financially literate indicator variable equals 0.13 ($s.e. = 0.037$). These estimates suggest that survival optimism's effect on savings rates is at least as large as the effect of financial literacy. After controlling for income and education in column 3, the estimate of $\beta_{1k}$ equals 0.14 ($s.e. = 0.033$), suggesting that most of the effect of survival beliefs on savings goes above and beyond any individual differences in economic circumstances. Using our alternative measure of subjective beliefs, *longevity.optimism*, leads to similar findings across the three specifications (columns 4 through 6).

The results are similar when we examine survival beliefs and savings draw down (Panel B). The coefficient on *survival.optimism* is between 0.20 and 0.23 across the three specifications and is statistically significant at the one percent error level (columns 1 - 3). This implies that a one standard deviation increase in survival optimism is associated with a 20 percent increase in the log odds of delaying the use of savings (e.g. from 6 - 10 years to at least 10 years from today). Similarly, the coefficient on *longevity.optimism* is around 0.09 and is statistically significant significant at the ten percent level across columns 4 through 6. Lastly, more optimistic survival beliefs even correlate positively with self-identified investing experience (Panel C).

To better illustrate the economic significance of the relation between survival optimism and savings rates, Figure 4 presents fitted estimates of a multinomial logit model analogous to equation 2. Moving from two standard deviations below to two standard deviations above the mean survival optimism decreases the respondents' likelihood of spending more than they earn from about 13 to 5 percent (Panel A). The likelihood of spending all of their monthly income falls from 40 to 24 percent, saving around ten percent increases from 33 to 50 percent, and saving around twenty-five percent increases from 11 to 17 percent. Likewise, for the same increase in survival optimism, respondents' likelihood of using their savings any time now decreases from 30 to 13 percent, in two to five years decreases from 35 to 23 percent, in six to ten years increases from 13 to 17 percent, and the likelihood of using savings at least ten years from now increases from 22 to 44 percent (Panel B).

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Retirees may benefit from leaving bequests, offering an alternative explanation for why many do not fully draw down their savings. Table 6 tests the relative contribution of bequests versus survival beliefs by estimating ordered logit estimates of equation 2, in which the dependent variable is the rate at which respondents draw down their savings. Specifically, these new tests include an additional independent variable, *expected.bequests*, equal to the chances from 0 to 100 that the respondent will leave an inheritance, normalized so that a one standard deviation increase equals a one unit increase. Furthermore, we focus these tests on the sample of respondents near and beyond retirement (58, 68, and 78-year-olds). Columns 1 and 4 include the sample of respondents with children, columns 2 and 5 include those without children, and columns 3 and 6 pool these samples. The variable of interest is *survival.optimism* in columns 1 through 3 and *longevity.optimism* in columns 4 through 6.

Survival beliefs are at least as important as bequest motives in determining the rate at which retirees draw down their savings. Across all specifications, the expected likelihood of leaving inheritances correlates positively with delayed use of one's savings (coefficient estimates equal to between 0.24 and 0.25 for the pooled sample) and the relationship is stronger for respondents with children (coefficient estimates equal to 0.26 for those with children and between 0.19 and 0.23 for those without children). Bolstering our confidence that mortality beliefs have a distinct effect on savings rates, the coefficients on our measure of survival optimism are positive in all specifications and statistically significant at the five percent error level in five of six regressions. Considering estimates from the pooled samples, in column 3, the coefficients on *survival.optimism* and *expected.bequests* equal 0.18 and 0.25. In column 6, the coefficients on *longevity.optimism* and *expected.bequests* equal 0.35 and 0.24. The similarly sized coefficients suggest that mortality beliefs and bequest motives make similar contributions to savings rates. A final notable feature of Table 6 is that the expected likelihood of delaying the use of personal savings declines in respondent age, suggesting that the dependent variable does a good job of representing savings drawn down during retirement.

# 3 Modeling the Life Cycle and Subjective Beliefs

This section presents our modeling framework, a canonical dynamic life-cycle model. We highlight in this framework how mortality beliefs impact the maximization problem as they enter the effective discount rate: while the first component of the effective discount rate is given by the constant rate of time preference, the second component is given by subjective transition probabilities. This connects the model directly to our empirical analysis where me measure these transition probabilities. Otherwise, we calibrate the model using standard parameters. The next section shows the dramatic effect that calibration to actual subjective transition probabilities has for consumption, savings, and portfolio choice in a canonical life-cycle model.

## 3.1 Model Setup

Our framework is based on Love (2013). Agents live in discrete time, where $t = 0, 1, 2, 3, ...T_{retire}, ..., T$ and $T_{retire}$ denotes the date of retirement. Agents choose to maximize their expected discounted stream of utility by choosing current period consumption, as well as what share of income to allocate to either a risky or risk-free asset. Recursively, their problem can be written as follows:

$$V_t^*(X_t, P_t) = \max_{C_t, \phi_t}\{u(C_t) + \beta s_t \mathbf{E_t}[V_{t+1}^*(X_{t+1}, P_{t+1})] + \beta(1 - s_t)\mathbf{E_t}[B_{t+1}(R_{t+1}(X_t - C_{t)}))]\}$$

where $C_t$ denotes consumption in period $t$, $\phi_t$ the share of wealth allocated to the risky asset, $P_t$ permanent income, $X_t$ cash on hand, $B_t(X_t)$ a bequest motive, $\beta$ the rate of time preference, and $s_t$ the subjective probability that individuals attach to transitioning to the next period conditional on having reached the current period. Cash on hand evolves as follows:

$$X_t = R_t(X_{t-1} - C_{t-1}) + Y_t$$

where the gross rate of return on the portfolio is the weighted return of the risky and the risk free asset, that is, $R_t = \phi_t R_t^r + (1 - \phi_t)R^f$.

The process for income $Y_t$ is given by permanent income $P_{t-1}$, an adjustment for the age-earnings profile $G_t$, a shock $N_t$ following a log-normal distribution and a transitory shock $\Theta_t$. This specification is due to Carroll (2011). Thus, we have that:

$$Y_t = P_{t-1} G_t N_t \Theta_t$$

and permanent income transitions according to:

$$P_t = P_{t-1} G_t N_t$$

We parameterize the utility function by choosing $u(C) = C^{1-\rho}/(1-\rho)$, and the bequest function by choosing $B(X) = b(X/b)^{(1-\rho)}/(1-\rho)$. The curvature of the utility function is $\rho$. We solve the problem numerically using the method of endogenous grid-points as described in Carroll (2011) and Love (2013).

We emphasize that subjective beliefs play an important role in this framework. Individual agents make their consumption and portfolio choices today using their subjective beliefs about their transitions to the next period. These beliefs multiplicatively enter the maximization problem through the effective period discount rate, that is, through $\beta s_t$. Thus, while the first component of the effective discount rate is given by $\beta$, the constant rate of time preference, the second component is exactly given by subjective transition probabilities.

## 3.2 Calibration

We calibrate our model to two specifications: one for comparison, one to show the effect of subjective beliefs, which can be further differentiated to yield additional comparisons. Our calibration for comparison purposes implements a canonical life-cycle model. This calibration is consistent with Love (2013) and we follow his parameter choices exactly except that we do not allow for an explicit bequest motive. Our subjective belief specification is identical to the comparison specification with one important difference: we now use subjective survival probabilities from our survey instead of statistical mortality data.

This difference in transition probabilities reflects the most important difference to the standard calibrations in the life-cycle literature because subjective beliefs affect the effective discount factor. Our main subjective belief calibration uses the subjective transition probabilities in Figure 2: on average, individuals who are between 28 and 38 years old believe that they are approximately 50 times less likely to live to the next period than statistical mortality data indicate. The comparison uses data from the 2007 Social Security Administration Period Life Tables. We set the rate of time preference $\beta$ equal to 0.98 in both specifications.

The other key parameter choices reflect standard values chosen in the life-cycle literature (Table 7). We refer the reader to Love (2013) for details as to why these parameters are chose. We thus set the risk-free rate equal to 2 percent, the excess return to 4 percent and the standard deviation of the risky asset to 18 percent. The excess return is somewhat lower than found by Campbell and Viceira (2002), which is needed so that households do not end up at a corner solution of investing 100 percent into the risky asset. This is helped by a high risk aversion parameter of 5. Following Love (2013) and Carroll and Samwick (1997), we use 1970-2007 PSID data to calibrate the income process. While there are potentially many interesting aspects to the life cycle coming from family composition and marital status, we calibrate the income process for college graduates only who live in a married household but without additional dependents. We allow for a non-zero correlation between permanent income and excess returns during the working life, but set the correlation to zero during retirement.

# 4 Life-cycle Model with Mortality Beliefs, Results

This section shows the dramatic impact that introducing subjective beliefs into a run-of-the-mill lifecycle model can have. First, we find that young individuals overconsume and undersave relative to what is optimal in a benchmark based on statistical transition probabilities. Second, we find that retirees consume less than would be optimal. This holds true even when we abstract from wealth differences due to undersaving when young.

First, we find that the introduction of subjective beliefs into a canonical life-cycle model has qualitatively and quantitatively large effects on consumption, savings and asset allocations of the young. Since this period is crucial for asset accumulation for retirement, we view the large effects during this period as our main result. What do we find exactly? During much of their working life, individuals substantially over-consume, relative to what our benchmark specification based on statistical probabilities implies (the top left panel of Figure 5). Between ages 28 and 58, people on average consume 25 percent more based on their subjective beliefs than what they should based on statistical transition probabilities. This is equivalent to $5000 per year.

The intuition for this result lies in the lower than statistical, subjective transition probabilities: due to these beliefs, people discount the future more and prefer present-term consumption. This is what the change of the effective discount factor implies. Unlike other work in the life-cycle literature such as Laibson (1997), we do not require any behavioral assumptions to obtain our results.

At the same time, a result of such large over-consumption is that people have less income to save and accumulate fewer assets when they are young. Their savings rate and total accumulated assets are below those implied by our canonical comparison model between ages 28 and 58. Then, as people approach retirement, we find that their consumption stays essentially flat. In particular, this means that their savings go up starting at age 58 since the income profile we calibrate to implies rising incomes until retirement. In fact, savings leading up to retirement are slightly higher than in the canonical model.

Second, an important finding is what happens during retirement. Strikingly, throughout retirement, people save more compared to the canonical model while they consume relatively less. Because they want to smooth consumption but cannot rely on a large asset base, this is an intuitive result. Interestingly, people have an approximately constant savings profile during retirement. They save on average \$17,500 per year. These results can be seen from the top right panel and the bottom left panel of Figure 5.

To what extent are the heavy right tails in subjective beliefs at old age responsible for higher savings during retirement? Figure 6 investigates this by comparing only the choices of retirees, either under subjective or statistical transition probabilities, while giving individuals exactly the same amount of assets at age 65. That is, we simulate a truncated version of the life-cycle model. We find that subjective transition probabilities still generate a pattern of oversaving and under-consumption during retirement, relative to a benchmark of statistical transition probabilities. This finding shows that not only a lower asset base at the start of retirement but again, subjective beliefs are crucial determinants of savings and consumption decisions.

## 4.1 Robustness

Our results are robust to a number of alternative parametrization, as well as alternative sets of subjective transition probabilities. Figure 7 presents evidence of the latter. The most notable differences are for subjects that have confidence in their answers to the subjective life-expectancy questions. For these individuals, the life-cycle model predicts overconsumption when young by an even greater amount. This leads to increased under-accumulation of wealth.

The results are insensitive to alternative discount factors (Figure A.1). When $\beta$ is increased, overconsumption of the young increases and wealth accumulation falls, implying an interaction between the discount factor and SLEs. When the coefficient of relative risk-aversion is changed from our preferred parametrization ($\rho = 5$), the model produces additional overconsumption for both increases and decreases in $\rho$ (Figure A.2). These differences are owing to changes in how individuals allocate their savings between the risky and risk-less asset. Lastly, we find little change in our results when we incorporate a bequest motive into the model (Figure A.3).

## 4.2 Subjective Beliefs and Asset Returns

Finally, our results relate to the asset pricing and finance literature, specifically the well-studied relation between the risk aversion and the difference between the returns on a risky and risk-less asset (Mehra and Prescott (1985)). As Siegel and Thaler (1997) summarize, an additively separable utility function with constant relative risk-aversion can be reduced to a single linear equation. The equation sets the equity premium (the return on the risky asset minus the risk-free rate) equal to the covariance between consumption and asset prices scaled by a single parameter, the coefficient of relative risk-aversion, $\rho$. Given what the data says about returns and consumption over time, the equation implies a value of $\rho = 30$. However, $\rho = 30$ also suggests that one would concede 49 percent of their wealth just to avoid a coin-flip gamble that would either double or half their existing wealth. Hence, the relationship is difficult to reconcile with observed risk-tolerance and is therefore deemed a puzzle.

There is evidence of a connection between mortality beliefs and the high levels of the equity premium. Figure 8 plots average wealth accumulation over the life-cycle for different levels of risk-tolerance, the equity premium, and two different survival functions – the actuarial data and the survey-elicited subjective belief distribution. We highlight the time-series of wealth accumulation calibrated to the actuarial survival data and with an equity premium of 4. The risk-free rate is determined by the discount factor, which we set equal to $1/\beta = 1.02$. Hence, the return on equity equals 6. This time-series is the welfare-maximizing set of outcomes over the life-cycle for a perfectly calibrated individual given these parameter values. In other words, it serves as our benchmark.

In comparison, we estimate the wealth-accumulation time-series using SLEs and vary the level of equity premium. When $\rho = 2$, the model solution using SLEs requires an equity premium close to 8 to come close to achieving benchmark levels of wealth. When $\rho = 4$, the required equity premium falls to around 6. For greater levels of $\rho$, specifically 10 and 20 in Figure 8, the consumer is invariant to the different levels of equity premium, and is seemingly equally well-off under the subjective and actuarial survival functions.

...

A more formal treatment, which uses GMM to estimate the return on equity, provides further evidence that these survival beliefs affect the required returns to holding equity. To estimate $R^r$, we search for the parameter value that minimizes the following objective function:

$$\min_{R^r} \quad \sum_{t=1}^{T} \left(X_t - \widehat{X}_t\right) \cdot \mathrm{I}_{\mathrm{T}\times\mathrm{T}} \cdot \sum_{t=1}^{T} \left(X_t' - \widehat{X}_t'\right)$$

where $X$ is a vector that includes the time-series of cash-on-hand at each age, $t$, of $i$'s life using the model solution with actuarial transition probabilities. The vector, $\widehat{X}$, is cash-on-hand when the individual has SLEs. We estimate $R^r$ holding constant different values of $\rho$ and $\beta$. The counter-factual exercise determines what the required excess return on equity would have had to have been to achieve equivalent levels of lifetime wealth accumulation when the individual has subjective mortality beliefs.

Estimates of $R^r$ show that individuals require higher levels of equity returns to compensate them for having mortality beliefs that differ from actuarial data (Figure 9). The figure presents the estimated $R^r$ for $\rho$ ranging from 1 to 10 and $\beta$ from 0.9 to 1. The top left graph presents the required return on equity needed to achieve an equivalent level of wealth accumulation as an individual without mistaken survival beliefs who receives an equity premium of 0.01. The top right is for an equity premium of 0.02, bottom left has 0.03, and the bottom right has 0.04.

The estimated equity premium increases under all of these different parameterizations when the representative agent has SLEs. The effect is often large. For instance, when we use $\beta = 0.98$ and $\rho = 2$, $R^r$ increases from 1 percent to around 10 percent when the individual goes from making decisions using actuarial data to their own subjective beliefs. Generally, the effect of these beliefs on the required return on equity lessens as $\beta$ decreases away from one. The effect on the equity premium has a concave relation to $\rho$.

## 4.3 Subjective Beliefs and Asset Returns in an OLG Model

An alternative method to fully exploit the tension between the beliefs of the young and those of the old is through an overlapping generations model. In the model, the young and the old can trade their endowments of the risky and riskless asset. The asset prices are derived from the stochastic Euler equations of the marginal investor in the equity and bond markets.

In the model, the superscripts $y$, $r$, and $o$ refer to the young, retiring, and old generations, respectively. The budget constraint for the young is

$$c_t^y + q_t^b b_t^y + q_t^e e_t^y = w_t^y.$$

where the price of a unit of equity ($e$) is $q_t^e$ and the price of a unit of the bond ($b$) is $q_t^b$. The budget constraint of the retiring is

$$c_{t+1}^r + q_{t+1}^b b_{t+1}^r + q_{t+1}^e e_{t+1}^r = w_{t+1}^r + \left(q_{t+1}^b + g\right) b_t^y + \left(q_{t+1}^e + d_{t+1}\right) e_t^y$$

where $d$ is a stochastic dividend payment and $g$ is the bond coupon. The budget constraint of the old aged is

$$c_{t+2}^o = q_{t+2}^b b_{t+1}^r + \left(q_{t+2}^e + d_{t+2}\right) e_{t+1}^r.$$

Further, the supply of equity and the supply of bonds across age cohorts each sum to one, such that the assets are in fixed supply.

The agent solves problem when young and commits to solution.

$$
\begin{aligned}
\max_{(c_t, c_{t+1}, c_{t+2}, b_t, b_{t+1}, e_t, e_{t+1})} \quad & U \quad \left(c_t^y\right) + \beta^y \mathrm{E} U\left(c_{t+1}^r\right) + \beta^y \beta^r \mathrm{E} U\left(c_{t+2}^o\right) \\
s.t. \quad & c_t^y + q_t^b b_t^y + q_t^e e_t^y = w_t^y \\
& c_{t+1}^r + q_{t+1}^b b_{t+1}^r + q_{t+1}^e e_{t+1}^r = w_{t+1}^r + \left(q_{t+1}^b + g\right) b_t^y + \left(q_{t+1}^e + d_{t+1}\right) e_t^y \\
& c_{t+2}^o = \left(q_{t+2}^b + g\right) b_{t+1}^r + \left(q_{t+2}^e + d_{t+2}\right) e_{t+1}^r
\end{aligned}
$$

From here, we refer readers to the paper's appendix for the model's solution, and to Constantinides et al. (2002) for any additional insights into the model and parameterization. The key ingredient is the correlation structure between aggregate expect output (the stochastic dividend) and the shares of wages going to the young and those prior to retirement. The young want to hedge against their future income uncertainty and so they prefer to hold equity, while those nearing retirement tilt their portfolio towards bonds.

Our insight is that the discount factors $\beta$ vary over the lifecycle and they reflect the agent's survival beliefs ($\beta \cdot \mathrm{E_t}\left[s_{t+1}\right]$). The biased beliefs of the young cause them to be more impatient (a reduction in $\beta^y$), while those around retirement become more patient (an increase in $\beta^r$).

...

Figure 10 presents results of the model's solution for the equity premium. The x-axis presents the difference between the subjective mortality beliefs of the old versus the young, with larger values indicating that the old are more optimistic about their survival than young people. Our primary finding is that as the old become more optimistic, we increase the patience of the generation around retirement age, and the equity premium rises. This occurs because the older generation is the marginal bond holder in the economy, so their Euler equation prices the bond. Hence, the equity premium rises through lower returns on the risk-free asset.

An appealing way to understand this relationship is to argue not that the return on equity is too high, but that historical bond returns are too low (Weil (1989)). This argument highlights the rate of time-preference, and draws into question whether observed asset (bond) returns are a reasonable reflection of the model-implied risk-free rate. Our subjective life-expectancies contribute to this line of inquiry, because they interact multiplicatively with the discount factor. Even in our more conservative estimates of SLEs, we show that with a transition probability of around 0.95, the weight put on the discounted stream of future consumption falls relative to today's consumption. This implies that the latent risk-free rate is actually much higher than is the case when only $\beta$ is used to discount. This upward adjustment to the risk-free rate lessens the differential between it and historical equity returns, which would be more consistent with lower levels of $\rho$. Another way to view this result is to note that there is room for an even greater divide between equity returns and $1/\beta$ once an adjustment has been made for subjective survival beliefs.[6]

# 5 Conclusion

This paper presents new findings on subjective survival beliefs over the life-cycle. Young people tend to overestimate their mortality risk while older individuals believe they will survive longer than actuarial data expect. We embed these survival beliefs into a canonical dynamic life-cycle model with portfolio choice. Without any modifications to the standard model and using the literature's preferred parametrization, the application of elicited survival beliefs better align the model with notable features of the data. Namely, our estimates produce under-saving while young and under-consumption while old. They also allow the model's solution to feature reasonable levels of elicited risk-tolerance and the historical equity premium. In sum, simply incorporating more accu-

[6] Our explanation bears similarity – either mechanically or in spirit – to a few other popular theories for the high return on equity. These theories include excessive pessimism (optimism) over expansions (contractions) (Cecchetti et al. (2000)), low-probability or tail events (Rietz (1988)), and pessimism and doubt over the growth rate of consumption (Abel (2002)). Our paper is perhaps most closely aligned with the latter explanation, because it also generates a reduction in the risk-free rate.

rate data on subjective beliefs, substantially improves the performance of the standard framework in a number of seemingly unrelated yet critical dimensions.

As a final consideration, we develop a deeper understanding as to why subjective survival beliefs are poorly aligned with actuarial probabilities. Our survey asks how respondents develop expectations of their own mortality. When developing their own survival beliefs, the average respondent places about half as much weight on unlikely occurrences such as natural disasters and animal attacks as they do on the natural course of aging and medical conditions. If that is indeed so, it is important that we more generally consider how beliefs diverge from true probability distributions, because there are important consequences for savings rates and asset returns.

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Table 1: **Survey Respondent Characteristics**

**Description:** This table presents data on the characteristics of participants in the survey administered by Qualtrics.

| | pct. | | pct. | | pct. |
|---|---|---|---|---|---|
| *age* | | *civil status* | | *gross hh income* | |
| 28 | 12.1 | single | 21.9 | less than \$10k | 7.0 |
| 38 | 24.6 | partner (not co-habitating) | 1.2 | \$10k - \$20k | 10.1 |
| 48 | 23.2 | partner (co-habiting) | 7.7 | \$20k - \$35k | 17.6 |
| 58 | 19.0 | married | 50.4 | \$35k - \$50k | 17.2 |
| 68 | 16.2 | divorced | 13.7 | \$50k - \$100k | 33.2 |
| 78 | 4.9 | widowed | 5.1 | \$100k - \$200k | 13.1 |
| | | | | greater than \$200k | 1.8 |
| *gender* | | *education* | | | |
| female | 51.9 | primary school | 1.8 | | |
| male | 48.2 | high school | 21.1 | | |
| | | college, no degree | 34.1 | | |
| *have children* | | bachelor's degree | 29.3 | | |
| no | 32.2 | master's degree | 11.3 | | |
| yes | 67.8 | doctorate | 2.4 | | |

$N = 4517$

Table 2: **Summary Statistics of Regression Variables**

**Description:** This table presents data on the summary statistics of participants in the survey administered by Qualtrics. *Survival optimism* equals the difference between the respondent's subjective belief about surviving at least $l = \{1, 2, 5, 10\}$ years and the actuarial probability according to the Social Security Administration, $E_{it}[surv(t+l)] - Pr_{it}[surv(t+l)]$, where $t$ is respondent $i$'s age. *Longevity optimism* equals the difference between the respondent's subjective longevity and the projected age of death according to the Social Security Administration.

| | mean | std dev | p25 | median | p75 |
|---|---|---|---|---|---|
| **mortality beliefs** | | | | | |
| survival optimism (ppt) | -9.12 | 19.76 | -13.46 | -0.80 | 0.96 |
| longevity optimism (years) | -2.16 | 13.09 | -8.30 | -2.10 | 4.50 |
| **savings rates** | | | | | |
| *share monthly income saved* | | | | | |
| ... rely on credit cards | 0.09 | | | | |
| ... spend all income | 0.32 | | | | |
| ... save ~ 10% | 0.42 | | | | |
| ... save ~ 25% | 0.14 | | | | |
| ... save $\geq$ 50% | 0.04 | | | | |
| *when plan to use savings?* | | | | | |
| ... any time now | 0.21 | | | | |
| ... 2 - 5 years from now | 0.29 | | | | |
| ... 6 - 10 years | 0.16 | | | | |
| ... at least 10 years | 0.34 | | | | |
| *investing experience* | | | | | |
| ... very inexperienced | 0.39 | | | | |
| ... somewhat inexperienced | 0.25 | | | | |
| ... somewhat experienced | 0.25 | | | | |
| ... experienced | 0.07 | | | | |
| ... very experienced | 0.03 | | | | |
| **personal attributes** | | | | | |
| *risk tolerance* | | | | | |
| ... willing to take substantial financial risk | 0.08 | | | | |
| ... above average | 0.22 | | | | |
| ... average | 0.37 | | | | |
| ... not willing to take financial risks | 0.33 | | | | |
| subjective likelihood of leaving bequest | 0.51 | 0.34 | 0.18 | 0.50 | 0.81 |
| financially literate ( = 1) | 0.68 | | | | |
| numerically literate ( = 1) | 0.56 | | | | |

$N = 4517$

## Table 3: **Risk Factors and the Formation of Mortality Beliefs**

**Panel I, Description:** This table presents data on the factors respondents use to judge their own survival probabilities. They are asked to rate each factor on a scale of 0 to 100 (the weights do not have to sum to one).

"When you assessed your survival likelihood, to what extent did you place weight on the following risk factors?" (scale of 0 to 100)

| variable | mean | median | std dev |
|---|---|---|---|
| The natural course of life and aging ("normal risk") | 73.69 | 80 | 23.79 |
| Medical conditions (e.g., cancer and heart disease) | 64.16 | 70 | 28.55 |
| Dietary habits (e.g. unhealthy foods) | 59.89 | 65 | 28.95 |
| Traffic accidents (e.g., car crash) | 43.12 | 44 | 29.08 |
| Physical violence (e.g., murder) | 31.22 | 20 | 30.04 |
| Natural disasters (e.g., earth quakes) | 31.72 | 20 | 29.68 |
| Animal attacks (e.g., shark attacks) | 21.67 | 9 | 28.79 |
| Risky lifestyle (e.g., base jumping) | 24.58 | 9 | 30.81 |
| "Freak events" (e.g., choking on your food) | 29.75 | 19 | 29.37 |
| | | | $N = 4517$ |

**Panel II, Description:** This table presents estimates of the following regression estimated using OLS: $risk.factor.weight_i = \beta_0 + \beta_1 \cdot survival.optimism_i + \sum_{l=0}^{5} \beta_{2l} age.category_i + \Gamma \cdot X_i + \varepsilon_i$. The dependent variable, $risk.factor.weight$, is equal to the weight respondent $i$ places on the corresponding risk factor divided by the sum of the weights $i$ places on all nine risk factors. The independent variable *survival optimism* equals $E_{it}\left[surv(t+l)\right] - Pr_{it}\left[surv(t+l)\right]$, where $t$ is respondent $i$'s age and $l = \{1,2,5,10\}$ (normalized so that a one unit increase equals a standard deviation increase), and survival probabilities are from the Social Security Administration. *Log num natural disaster deaths in zip code* equals the natural logarithm of one plus the number of deaths by natural disaster in a a respondent's zip code between 2001 and 2010 according to the Spatial Hazard Events and Losses Database (SHELDUS). We map the counties in SHELDUS to zip codes using the 2010 concordance from the Missouri Census Data Center. Standard errors clustered by respondent age are in parentheses, and ***, **, * denote statistical significance at the $p < 0.10$, $p < 0.05$, $p < 0.01$ levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| risk factor weight share | natural aging | medical | diet | traffic accident | violence | natur. disaster | animal attack | risky lifestyle | freak events |
| survival optimism (Z) | 3.458*** | -0.180 | 1.114*** | -0.303** | -0.772*** | -0.812*** | -0.705** | -0.615** | -0.932*** |
| | (0.10) | (0.27) | (0.18) | (0.094) | (0.17) | (0.058) | (0.19) | (0.19) | (0.073) |
| *age = 28, omitted* | | | | | | | | | |
| age = 38 | -0.261** | 1.900*** | 1.601*** | -0.220*** | -0.648*** | -0.581*** | -0.487*** | -0.445*** | -0.923*** |
| | (0.082) | (0.12) | (0.050) | (0.025) | (0.056) | (0.044) | (0.073) | (0.062) | (0.034) |
| age = 48 | 0.302** | 3.009*** | 1.536*** | -0.322*** | -0.492*** | -0.784*** | -0.903*** | -1.086*** | -1.323*** |
| | (0.089) | (0.13) | (0.048) | (0.032) | (0.059) | (0.049) | (0.075) | (0.063) | (0.038) |
| age = 58 | 1.300*** | 4.784*** | 3.678*** | -0.573*** | -1.332*** | -1.654*** | -1.819*** | -2.257*** | -2.182*** |
| | (0.057) | (0.081) | (0.044) | (0.018) | (0.043) | (0.022) | (0.056) | (0.050) | (0.025) |
| age = 68 | 1.576*** | 8.327*** | 5.894*** | 0.281*** | -1.297*** | -1.141*** | -1.584*** | -2.622*** | -1.630*** |
| | (0.095) | (0.13) | (0.054) | (0.027) | (0.066) | (0.042) | (0.083) | (0.069) | (0.037) |
| age = 78 | 4.709*** | 9.604*** | 7.299*** | -0.447*** | -2.492*** | -2.206*** | -2.252*** | -3.274*** | -3.402*** |
| | (0.080) | (0.018) | (0.031) | (0.029) | (0.021) | (0.036) | (0.013) | (0.021) | (0.023) |
| male ( = 1) | -1.020** | -0.424 | -0.754*** | -0.585** | 0.371 | 0.118 | 0.476* | 1.095*** | 0.571** |
| | (0.39) | (0.40) | (0.16) | (0.17) | (0.19) | (0.24) | (0.21) | (0.17) | (0.16) |
| log num natural disaster deaths in zip code | 0.509 | -0.577 | -0.285 | -0.173 | -0.0326 | 0.925*** | 0.0719 | -0.188 | 0.167 |
| | (0.65) | (0.40) | (0.56) | (0.17) | (0.30) | (0.18) | (0.13) | (0.14) | (0.28) |
| survival horizon FE | x | x | x | x | x | x | x | x | x |
| survival & longevity information treatments | x | x | x | x | x | x | x | x | x |
| average risk factor weight share | 23.47 | 18.97 | 17.09 | 11.22 | 7.03 | 7.32 | 4.35 | 5.15 | 6.95 |
| $N$ | 4517 | 4517 | 4517 | 4517 | 4517 | 4517 | 4517 | 4517 | 4517 |
| $R^2$ | 0.056 | 0.065 | 0.065 | 0.0052 | 0.036 | 0.033 | 0.055 | 0.059 | 0.042 |

## Table 4: **Rare Event Deaths and Mortality Beleifs**

**Description:** This table presents estimates of a Poisson regression. The dependent variables are respondents' estimates of the number of Americans who die in plane crashes annually or the number of people of struck by lightning in a given year. The independent variable *survival optimism* equals $E_{it}\left[surv(t+l)\right]-Pr_{it}\left[surv(t+l)\right]$, where $t$ is respondent $i$'s age and $l=\{1,2,5,10\}$ (normalized so that a one unit increase equals a standard deviation increase), and survival probabilities are from the Social Security Administration. *Numerical literacy* equals one if the respondent can correctly calculate probabilities. (Z) indicates that a variable is normalized such that a one unit increase equals a one standard deviation increase. Robust standard errors clustered by respondent age are in parentheses, and ***, **, * denote statistical significance at the $p<0.10$, $p<0.05$, $p<0.01$ levels, respectively.

| *Poisson regression dep var =* | subjective assessment of annual plane crash deaths | | subjective assessment of num. struck by lightning | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| survival optimism (Z) | -0.0936*** | -0.0934*** | 0.0463 | 0.0374 |
| | (0.014) | (0.015) | (0.045) | (0.047) |
| *age = 28, omitted* | | | | |
| age = 38 | -0.0807*** | -0.0807*** | 0.262*** | 0.260*** |
| | (0.014) | (0.014) | (0.016) | (0.017) |
| age = 48 | -0.0497*** | -0.0497*** | 0.245*** | 0.247*** |
| | (0.013) | (0.013) | (0.017) | (0.016) |
| age = 58 | -0.279*** | -0.279*** | 0.253*** | 0.238*** |
| | (0.012) | (0.014) | (0.026) | (0.032) |
| age = 68 | -0.411*** | -0.411*** | 0.231*** | 0.217*** |
| | (0.013) | (0.013) | (0.018) | (0.023) |
| age = 78 | -0.658*** | -0.658*** | -0.0765** | -0.0823** |
| | (0.032) | (0.031) | (0.032) | (0.034) |
| male ( = 1) | -0.301*** | -0.301*** | 0.0486 | 0.0327 |
| | (0.088) | (0.085) | (0.043) | (0.038) |
| numerical literacy ( = 1) | | -0.00327 | | 0.159* |
| | | (0.049) | | (0.095) |
| survival horizon FE | x | x | x | x |
| education FE | x | x | x | x |
| income FE | x | x | x | x |
| mean of dependent variable | 626.0 | 626.0 | 670.6 | 670.6 |
| *N* | 4515 | 4515 | 4187 | 4187 |
| pseudo $R^2$ | 0.026 | 0.026 | 0.018 | 0.019 |

# Table 5: **Mortality Beliefs and Savings Rates**

**Description:** This table presents results from estimating ordered logistic models. Coefficients give the ordered log-odds of moving to a higher category of the dependent variable. The independent variable *survival optimism* equals respondent *i*'s belief in the probability they survive at least *x* number of years minus the statistical probability of survival according to the Social Security Administration (SSA) actuarial tables. *Longevity optimism* is the respondent's beliefs about the age at which they will die minus the age-gender-conditional expected longevity according to the SSA. *Financially literate* equals one if *i* correctly answers at least 2 out of 3 of the financial literacy survey questions from Lusardi and Mitchell (2011). (Z) indicates that a variable has been normalized so that a one unit increase equals a one standard deviation increase. All regression include controls for the respondent's gender, age, survival horizon (experimental treatments for the probability of living at least $x$ number of years, where $x \in \{1,2,5,10\}$), indicators for respondents treated with age-cohort-specific information about survival probabilities and expected longevity, an indicator for numerical literacy, and the respondents' risk-tolerance. Standard errors clustered by respondent age are in parentheses, and ***, **, * denote statistical significance at the $p < 0.10$, $p < 0.05$, $p < 0.01$ levels, respectively.

| **Panel A** | *ordered logit dep var* = frac. monthly income saved | | | | | |
|---|---|---|---|---|---|---|
| | (1a) | (2a) | (3a) | (4a) | (5a) | (6a) |
| survival optimism (Z) | 0.191*** | 0.187*** | 0.139*** | | | |
| | (0.034) | (0.035) | (0.033) | | | |
| longevity optimism (Z) | | | | 0.159** | 0.159** | 0.121** |
| | | | | (0.069) | (0.069) | (0.059) |
| financially literate ( = 1) | | 0.130*** | 0.00952 | | 0.158*** | 0.0278 |
| | | (0.037) | (0.049) | | (0.038) | (0.052) |
| education FE | | | x | | | x |
| income FE | | | x | | | x |
| *base category*: rely on credit cards | | | | | | |
| ... spend all income | -2.356*** | -2.319*** | -1.401*** | -2.247*** | -2.205*** | -1.243*** |
| ... save ~ 10% | -0.316 | -0.278 | 0.732*** | -0.215 | -0.171 | 0.886*** |
| ... save ~ 25% | 1.704*** | 1.743*** | 2.885*** | 1.802*** | 1.848*** | 3.039*** |
| ... save $\geq$ 50% | 3.378*** | 3.417*** | 4.620*** | 3.479*** | 3.524*** | 4.776*** |

| **Panel B** | *ordered logit dep var* = when do you plan to use savings? | | | | | |
|---|---|---|---|---|---|---|
| | (1b) | (2b) | (3b) | (4b) | (5b) | (6b) |
| survival optimism (Z) | 0.231*** | 0.223*** | 0.201*** | | | |
| | (0.015) | (0.017) | (0.017) | | | |
| longevity optimism (Z) | | | | 0.0897* | 0.0924* | 0.0795* |
| | | | | (0.052) | (0.050) | (0.045) |
| financially literate ( = 1) | | 0.345*** | 0.275*** | | 0.374*** | 0.297*** |
| | | (0.098) | (0.10) | | (0.096) | (0.10) |
| education FE | | | x | | | x |
| income FE | | | x | | | x |
| *base category*: any time now | | | | | | |
| ... 2 - 5 years from now | -0.282* | -0.192 | 0.111 | -0.126 | -0.0351 | 0.373 |
| ... 6 - 10 years | 1.179*** | 1.275*** | 1.591*** | 1.320*** | 1.418*** | 1.841*** |
| ... at least 10 years | 1.865*** | 1.966*** | 2.298*** | 1.999*** | 2.103*** | 2.543*** |

| **Panel C** | *ordered logit dep var* = experience investing | | | | | |
|---|---|---|---|---|---|---|
| | (1c) | (2c) | (3c) | (4c) | (5c) | (6c) |
| survival optimism (Z) | 0.0796*** | 0.0724** | 0.0203 | | | |
| | (0.031) | (0.030) | (0.032) | | | |
| longevity optimism (Z) | | | | 0.0945*** | 0.100*** | 0.0479* |
| | | | | (0.031) | (0.030) | (0.027) |
| financially literate ( = 1) | | 0.316*** | 0.169** | | 0.331*** | 0.175** |
| | | (0.098) | (0.080) | | (0.097) | (0.080) |
| education FE | | | x | | | x |
| income FE | | | x | | | x |
| *base category*: very inexperienced | | | | | | |
| ... somewhat inexperienced | -0.950*** | -0.842*** | 0.0229 | -0.891*** | -0.783*** | 0.0459 |
| ... somewhat experienced | 0.297** | 0.411** | 1.334*** | 0.357** | 0.471** | 1.357*** |
| ... experienced | 2.033*** | 2.150*** | 3.166*** | 2.093*** | 2.211*** | 3.190*** |
| ... very experienced | 3.227*** | 3.344*** | 4.424*** | 3.288*** | 3.407*** | 4.448*** |
| *N* | 4517 | 4517 | 4517 | 4517 | 4517 | 4517 |

Table 6: **The Effect of Mortality Beliefs and Bequests on Savings Draw Down**

**Description:** This table presents results from estimating ordered logistic models. Coefficients give the ordered log-odds of moving to a higher category of the dependent variable. The independent variable *year-to-year survival rate beliefs* equals respondent *i*'s belief in the probability they survive at least $x$ number of years minus the statistical probability of survival according to the Social Security Administration (SSA) actuarial tables. *Longevity beliefs* is the respondent's beliefs about the age at which they will die minus the age-gender-conditional expected longevity according to the SSA. *Financially literate* equals one if *i* correctly answers at least 2 out of 3 of the financial literacy survey questions from Lusardi and Mitchell (2011). (Z) indicates that a variable has been normalized so that a one unit increase equals a one standard deviation increase. All regression include controls for the respondent's gender, survival horizon (experimental treatments for the probability of living at least $x$ number of years, where $x \in \{1,2,5,10\}$), indicators for respondents treated with age-cohort-specific information about survival probabilities and expected longevity, indicators for numerical literacy and financial literacy, and the respondents' risk-tolerance. Standard errors clustered by respondent age are in parentheses, and ***, **, * denote statistical significance at the $p < 0.10$, $p < 0.05$, $p < 0.01$ levels, respectively.

| | *ordered logit dep var* = when do you plan to use savings? | | | | | |
|---|---|---|---|---|---|---|
| *sample:* | has children | no children | pooled | has children | no children | pooled |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| survival optimism (Z) | 0.251*** | 0.0113 | 0.182*** | | | |
| | (0.047) | (0.084) | (0.030) | | | |
| longevity optimism (Z) | | | | 0.348** | 0.385*** | 0.346*** |
| | | | | (0.14) | (0.061) | (0.065) |
| expected bequests (Z) | 0.255*** | 0.230*** | 0.248*** | 0.263*** | 0.193*** | 0.240*** |
| | (0.098) | (0.038) | (0.055) | (0.087) | (0.028) | (0.057) |
| *age = 58, omitted* | | | | | | |
| age = 68 | -0.641*** | -0.875*** | -0.688*** | -0.619*** | -0.903*** | -0.682*** |
| | (0.059) | (0.029) | (0.031) | (0.040) | (0.017) | (0.021) |
| age = 78 | -0.836*** | -1.204*** | -0.892*** | -0.795*** | -1.235*** | -0.877*** |
| | (0.063) | (0.079) | (0.0044) | (0.018) | (0.053) | (0.025) |
| has children ( = 1) | | | -0.0820 | | | -0.0379 |
| | | | (0.13) | | | (0.14) |
| *base category*: any time now | | | | | | |
| ... 2 - 5 years from now | -2.099*** | -1.594*** | -2.094*** | -1.772*** | -1.641*** | -1.848*** |
| ... 6 - 10 years | -0.658* | -0.343 | -0.727** | -0.342 | -0.376** | -0.481 |
| ... at least 10 years | 0.435 | 0.530* | 0.290 | 0.753*** | 0.511*** | 0.541** |
| *N* | 1301 | 489 | 1790 | 1301 | 489 | 1790 |
| pseudo $R^2$ | 0.057 | 0.056 | 0.050 | 0.056 | 0.063 | 0.051 |

Table 7: **Life-cycle Model Baseline Parameters**

**Description:** This table presents the parameters used in the baselines version of the life-cycle model.

| **Parameter** | **Value** |
|---|---|
| Risk aversion ($\rho$) | 5 |
| Bequest parameter ($b$) | 2.5 |
| Discount factor ($\beta$) | 0.98 |
| Risk-free rate ($R^f$) | 2% |
| Equity premium ($R^e_t - R^f$) | 4% |
| Retirement age ($T^R$) | 65 |
| Maximum age ($T$) | 95 |
| Uncertain income in retirement? | no |
| Bequest motive? | no |

Figure 1: **Mortality Beliefs and Financial Planning**

**Description:** This figure displays the inputs into a personal financial plan used by the online investment service Betterment.

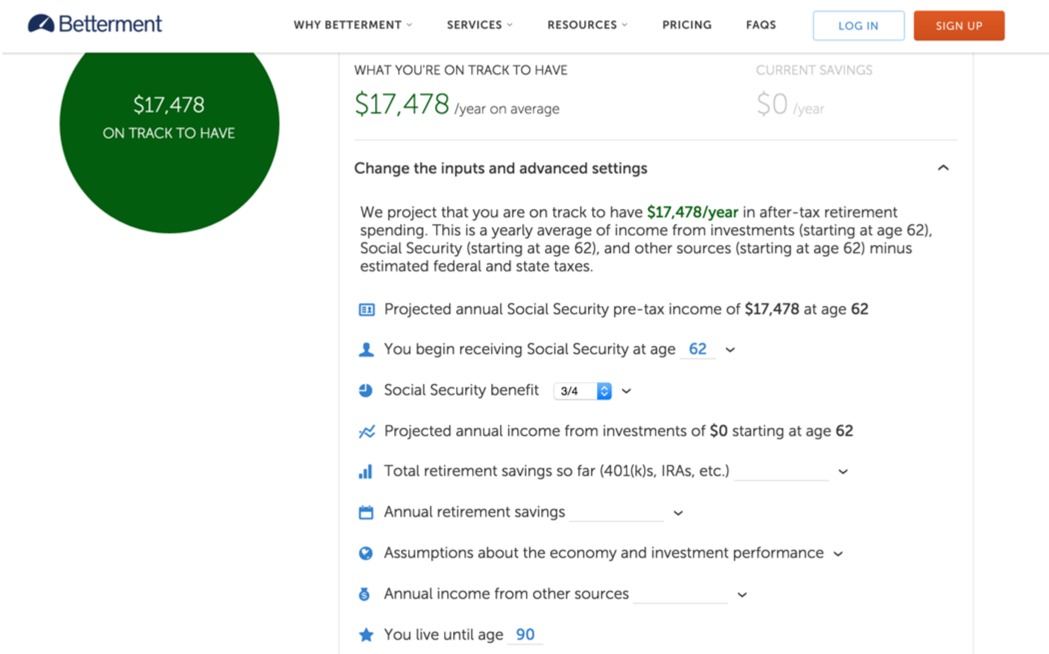


Figure 2: **Survival Beliefs vs. Actuarial Data**

**Description:** The figure compares elicited survival beliefs ("subjective survival prob.") against actuarial probabilities from statistical life tables provided by the Social Security Administration. We sample respondents age 28, 38, 48, 58, 68, and 78 ask them the probability that they will survive beyond 1, 2, 5, and 10 years. We ask an equal number of respondents (one-fifth each) about survival beyond 1 year, 2 year, 5 year, 10 year, and all horizons jointly.

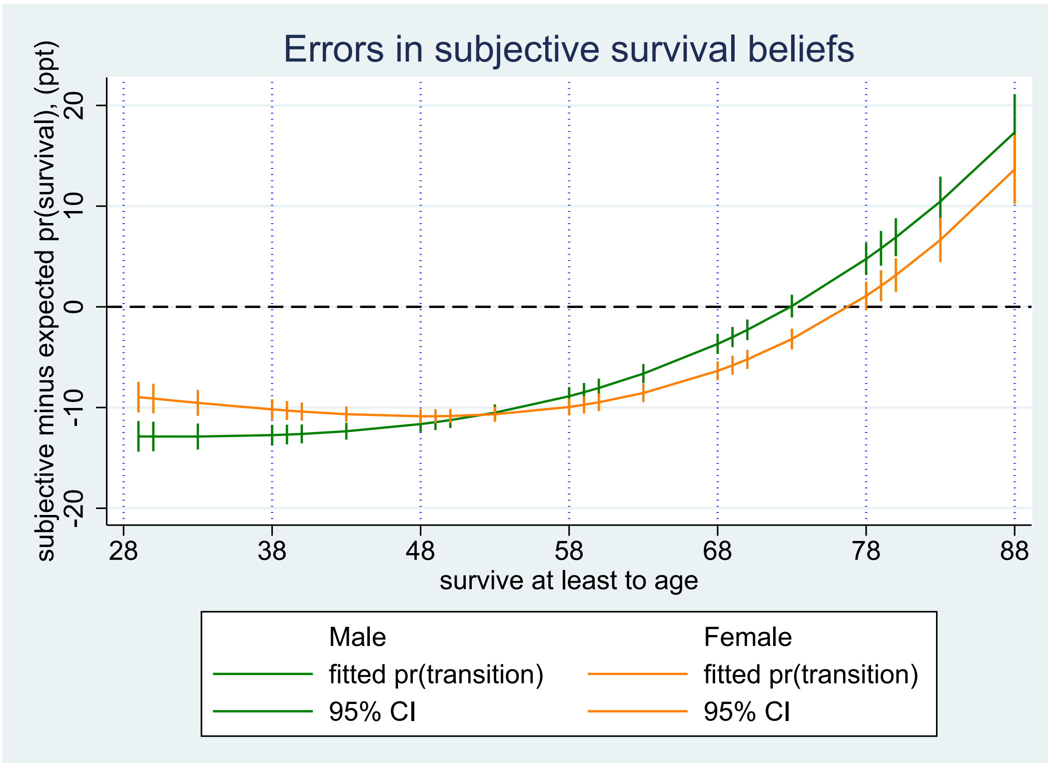
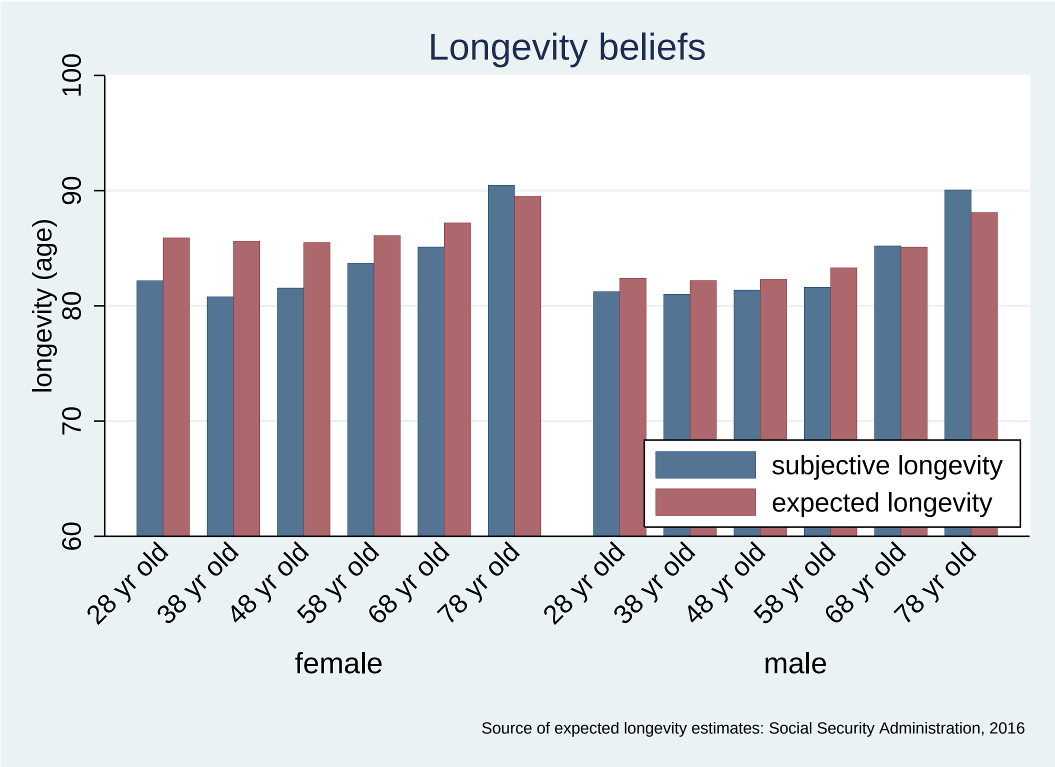


Figure 3: **Longevity Beliefs vs. Actuarial Data**

**Description:** The figure compares subjected longevity beliefs to expected longevity drawn from actuarial probabilities from statistical life tables provided by the Social Security Administration. We sample respondents age 28, 38, 48, 58, 68, and 78 and ask, "About how long do you think you will live? Please indicate the age that you expect to reach."



## Figure 4: **Mortality Beliefs and Savings Rates**

**Figure A, Description:** The figure presents the predictions from the following multinomial logistic model: $f(k,i) = \beta_{0k} + \beta_{1k} survival.optimism_{1i} + \beta_k X_i$, where $f(k,i)$ is a prediction of the probability that observation $i$ has outcome $k$. The dependent variable is the survey question: "How much of your monthly income do you save? (choose the closest answer from the following)", with the following set of possible responses: 1) "I spend more money than I earn. I often use credit cards or other loans to supplement my monthly income", 2) "I save around 25% of my monthly income", 3) "I save around 10% of my monthly income", 4) "I spend all of my income each month", or 5) "I save at least 50% of my monthly income." The coefficient $\beta_{1k}$ captures the effect of *survival.optimism* on the the likelihood of choosing $k$, and it equals $E_{it}[surv(t+l)] - Pr_{it}[surv(t+l)]$, standardized so that a one standard deviation increase equals a one unit increase. The matrix $X_i$ includes $i$'s age, gender, income, education, a categorical adjustment for the survival horizon, an indicator if $i$ was asked to consecutively provide her subjective beliefs about the four different survival horizons, and an indicator if $i$ correctly answers our numeracy test. Standard errors are clustered to allow for correlated residuals by age.


**Figure B, Description:** The dependent variable is the survey question: "When do you expect to use most of the money you are now accumulating in your investments or savings?" The set of possible answers are: 1) "At any time now...so a high level of liquidity is important", 2) "Probably in the future...2-5 years from now", 3) "In 6-10 years", and 4) "Probably at least 10 years from now."

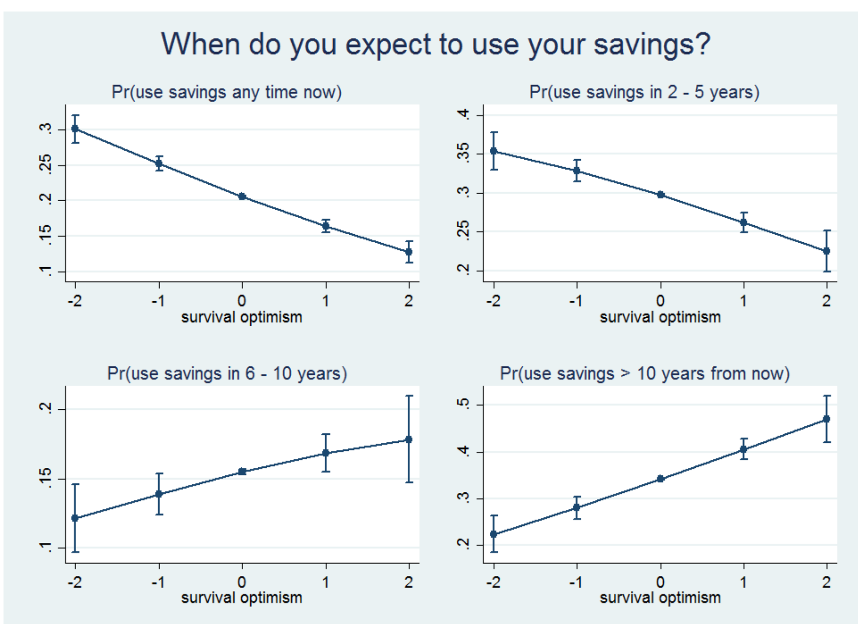


Figure 5: **Life-Cycle Results: Subjective vs. Actual Life-Expectancies**

**Description:** This figure presents the solution to the life-cycle outlined in Section 3. The line "SSA" takes the survival rates from the Social Security Administration. The dotted line, "Subj. Pr(Surv)", are model estimates using survey elicited subjective survival beliefs.

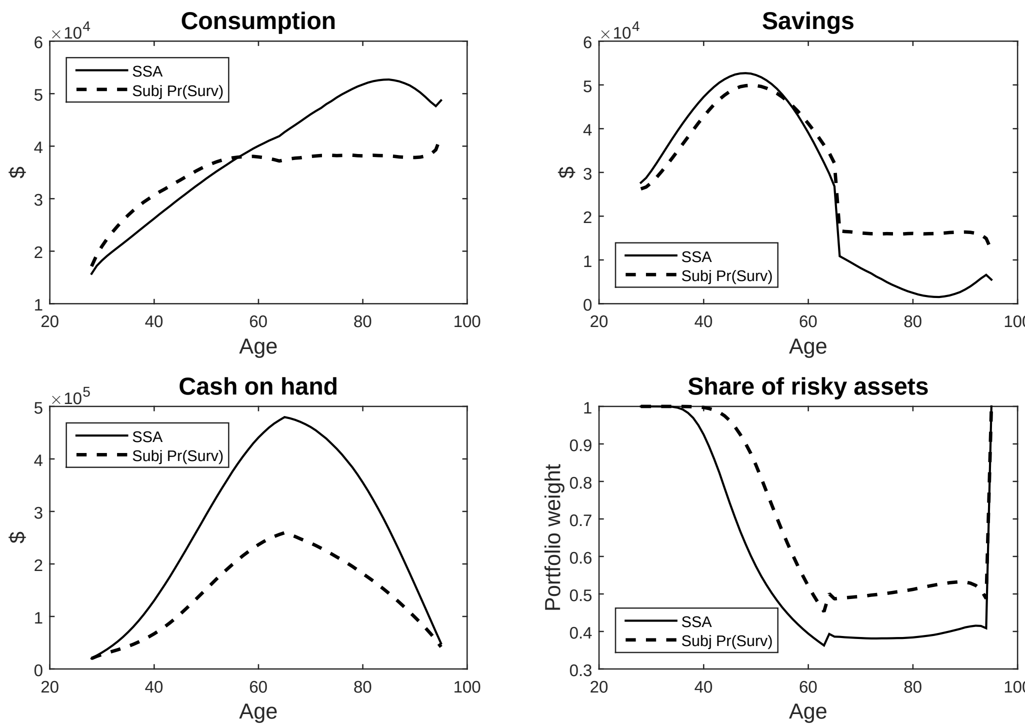


Figure 6: **Savings and Consumption During Retirement: Subjective vs. Actual Life-Expectancies**

**Description:** This figure presents the solution to the life-cycle outlined in Section 3. The model is solved using survey-elicited subjective survival beliefs. We allow the representative consumer to arrive at retirement (age 65) with $525,000 accumulate wealth, which is roughly the median household in 2008, excluding housing equity and including Social Security income. We also allow consumers to plan as though they will live until 120.

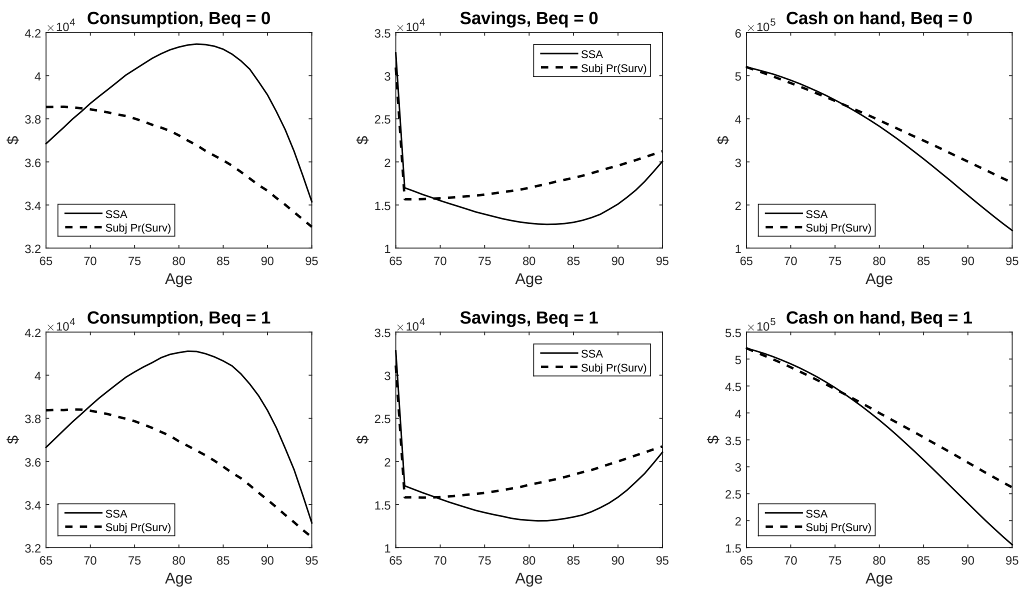


Figure 7: **Robustness to Different Subjective Beliefs**

**Description:** This figure presents the solution to the life-cycle outlined in Section 3. The model is solved using different sets of survey-elicited subjective survival beliefs, as described in Section 7.

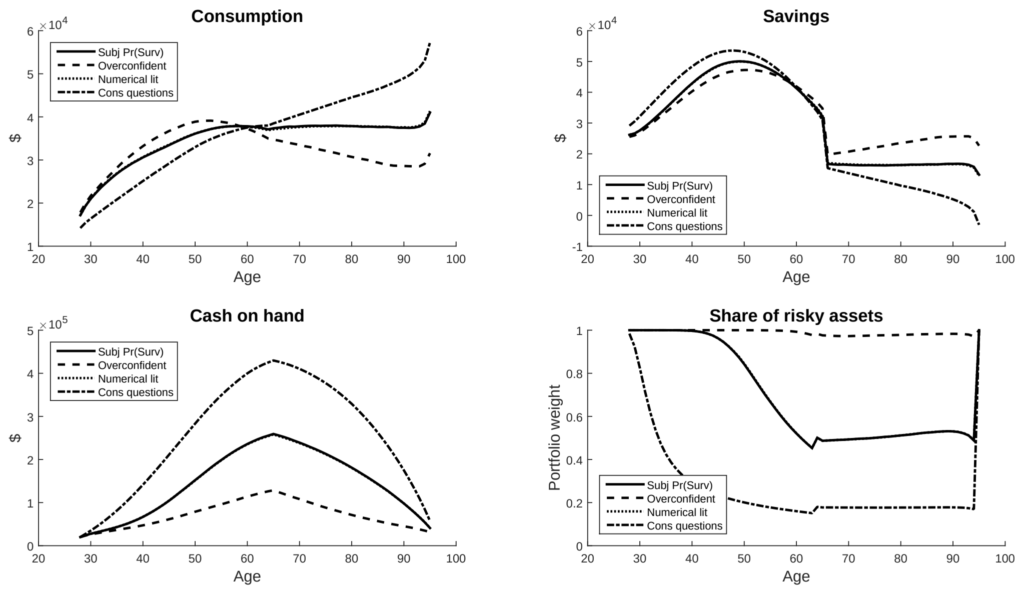


Figure 8: **Wealth Accumulation with Subjective Survival Beliefs and Different Levels of Equity Premium**

**Description:** This figure presents the solution to the life-cycle model outlined in Section 3. The model is solved using actuarial probabilities from the Social Security Administration (SSA). All other lines come from model solutions using the subjective survival beliefs in the Qualtrics survey, while employing different levels of the equity premium.

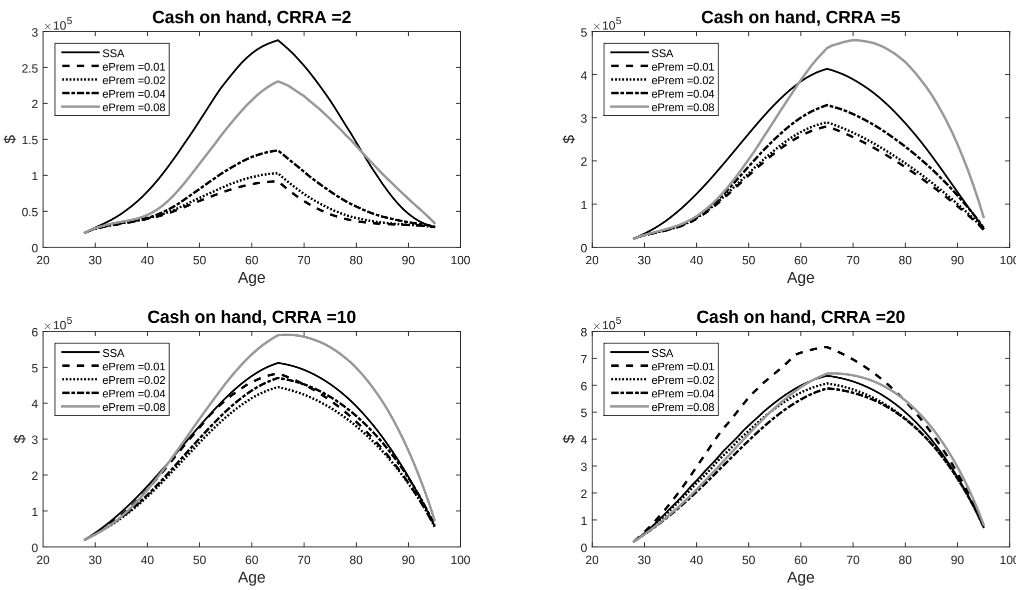


Figure 9: **Estimated Equity Premium with Subjective Mortality Beliefs**

**Description:** This figure presents estimated values of the excess return on equity. Estimates come from targeting life-time wealth accumulation in a life-cycle model with actuarial survival probabilites under different discount factors, levels of risk tolerance, and baseline return on equity (from top right to bottom left, 0.01, 0.02, 0.03, and 0.04). We estimate the required return on equity to match this wealth accumulation when the average consumer has subjective life-expectancies, while holding constant the consumer's decision rules.

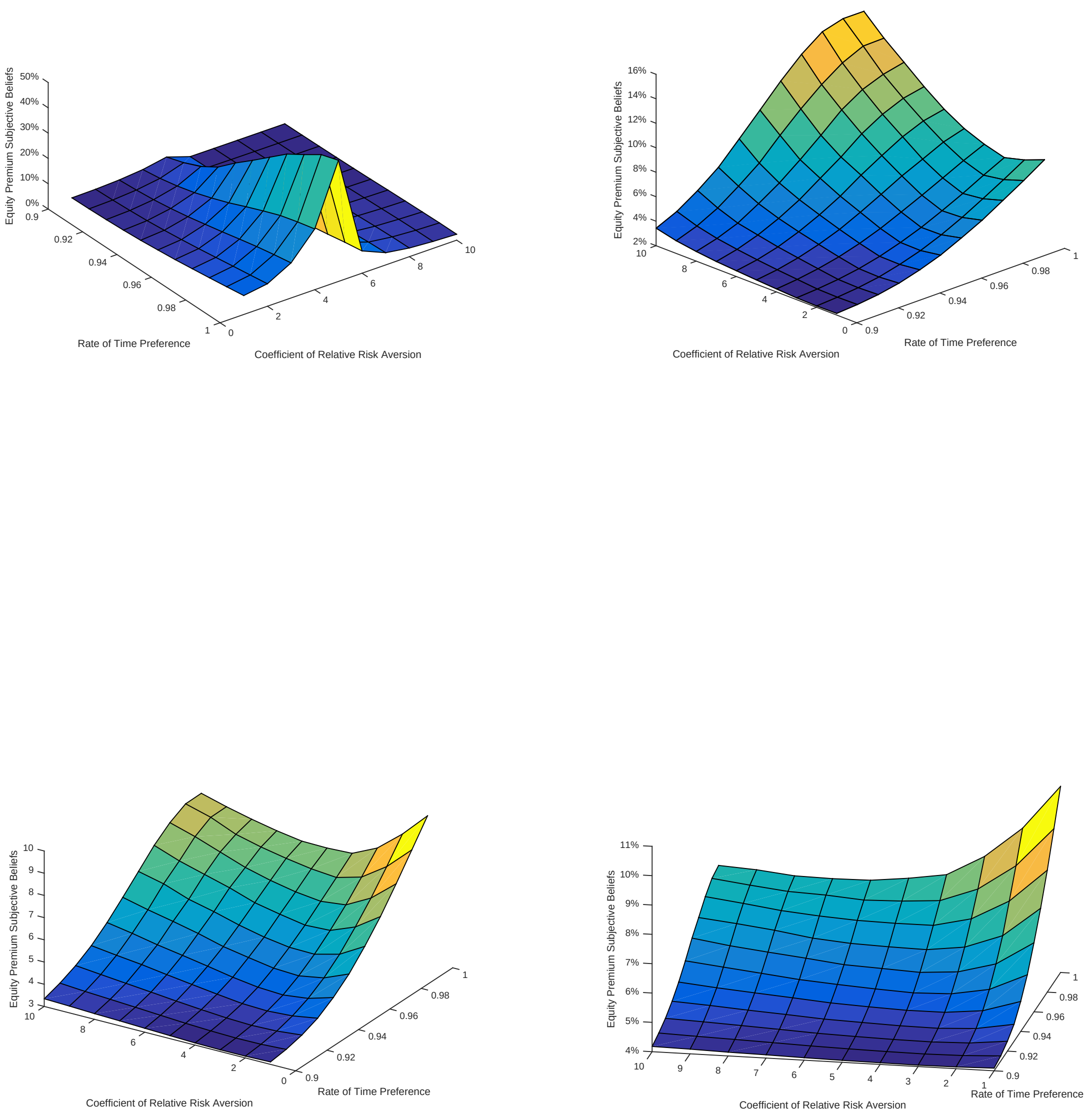
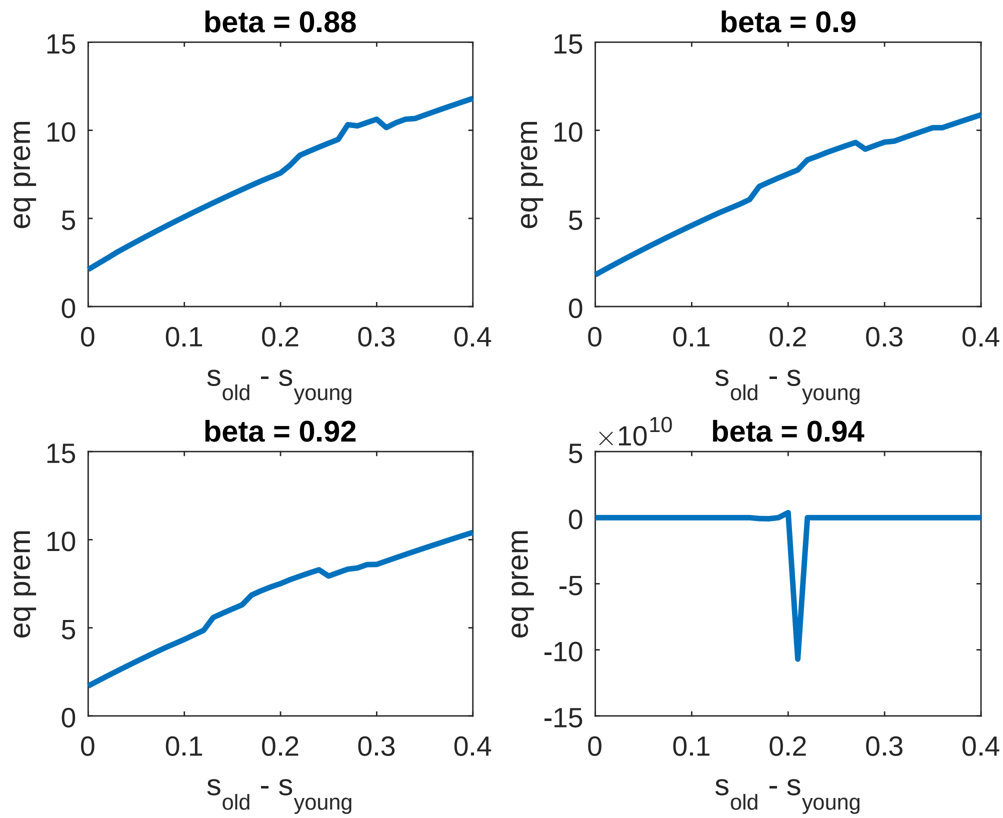


Figure 10: **The Risk Free Rate from an OLG model with Discount Factors that Vary by Age**
**Description:** This figure presents the risk free rate from the OLG model outlined in Section 3. In the model, the discount factors of the young and those nearing retirement are allowed to vary.



# Online Appendix:

# YOLO: Mortality Beliefs and Household Finance Puzzles

Not intended for publication

# A1: Robustness of Survival Beliefs

Table A.1: **Robustness of Mortality Belief Errors Over the Life-cycle**

**Description:** This table presents OLS regression results. In Panel A, *target age* is the respondent's current age plus survival target years, $x \in \{1,2,5,10\}$. In Panel B, *age* is the respondent's current age. Standard errors are in parentheses, and ***, **, * denote statistical significance at the $p < 0.10$, $p < 0.05$, $p < 0.01$ levels, respectively.

| **Panel A** | *dep var* = survival optimism (ppt) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1a) | (2a) | (3a) | (4a) | (5a) | (6a) | (7a) |
| target age squared | 0.00511*** | 0.00512*** | 0.00517*** | 0.00509*** | 0.00493*** | 0.00422*** | 0.00430*** |
| | (0.0014) | (0.0014) | (0.0014) | (0.0014) | (0.0014) | (0.0013) | (0.0013) |
| target age | -0.354** | -0.355** | -0.360** | -0.362** | -0.339** | -0.255* | -0.272* |
| | (0.16) | (0.16) | (0.16) | (0.15) | (0.16) | (0.15) | (0.15) |
| actuarial probabilities info treatment ( = 1) | | -0.408 | | | | | -0.374 |
| | | (0.59) | | | | | (0.56) |
| all survival horizons treatment ( = 1) | | | 1.614** | | | | 1.326** |
| | | | (0.65) | | | | (0.62) |
| numerical literacy ( = 1) | | | | 4.414*** | | | 4.393*** |
| | | | | (0.58) | | | (0.56) |
| smoker ( = 1) | | | | | -1.128 | | 0.0684 |
| | | | | | (0.70) | | (0.66) |
| subjective health assessment (Z) | | | | | | 5.877*** | 5.869*** |
| | | | | | | (0.34) | (0.34) |
| gender | x | x | x | x | x | x | x |
| education FE | x | x | x | x | x | x | x |
| income FE | x | x | x | x | x | x | x |
| $N$ | 4517 | 4517 | 4517 | 4517 | 4515 | 4510 | 4508 |
| $R^2$ | 0.066 | 0.066 | 0.067 | 0.078 | 0.067 | 0.15 | 0.17 |

| **Panel B** | *dep var* = longevity optimism (years) | | | | | | |
|---|---|---|---|---|---|---|---|
| | (1b) | (2b) | (3b) | (4b) | (5b) | (6b) | (7b) |
| respondent age squared | 0.00275** | 0.00278*** | 0.00275** | 0.00275** | 0.00213* | 0.00188* | 0.00147 |
| | (0.0011) | (0.0011) | (0.0011) | (0.0011) | (0.0011) | (0.0010) | (0.0011) |
| respondent age | -0.307*** | -0.311*** | -0.308*** | -0.307*** | -0.259** | -0.215* | -0.185 |
| | (0.12) | (0.12) | (0.12) | (0.12) | (0.12) | (0.11) | (0.11) |
| actuarial probabilities info treatment ( = 1) | | -1.290*** | | | | | -1.247*** |
| | | (0.45) | | | | | (0.43) |
| all survival horizons treatments ( = 1) | | | 0.861 | | | | 0.715 |
| | | | (0.57) | | | | (0.54) |
| numerical literacy ( = 1) | | | | -0.0160 | | | -0.134 |
| | | | | (0.47) | | | (0.45) |
| smoker ( = 1) | | | | | -3.029*** | | -2.347*** |
| | | | | | (0.56) | | (0.55) |
| subjective health assessment (Z) | | | | | | 4.154*** | 4.078*** |
| | | | | | | (0.24) | (0.24) |
| gender | x | x | x | x | x | x | x |
| education FE | x | x | x | x | x | x | x |
| income FE | x | x | x | x | x | x | x |
| $N$ | 4517 | 4517 | 4517 | 4517 | 4515 | 4510 | 4508 |
| $R^2$ | 0.036 | 0.037 | 0.036 | 0.036 | 0.043 | 0.11 | 0.12 |

# A2: Life-cycle Model Robustness to Alternative Parameter Choices

Figure A.1: **Subjective Survival Beliefs and Different Discount Factors**
**Description:** This figure presents the solution to the life-cycle outlined in Section 3. The model is solved using survey-elicited subjective survival beliefs.

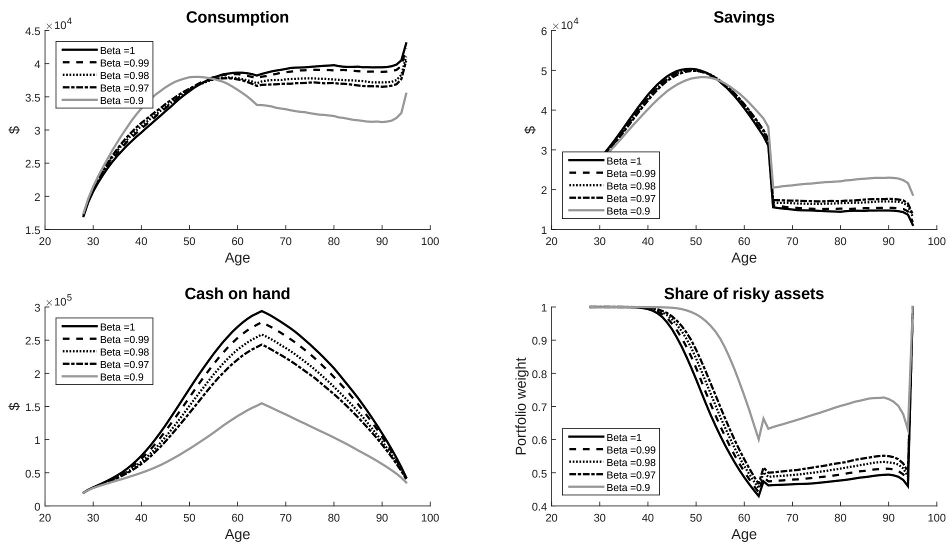



Figure A.2: **Subjective Survival Beliefs and Different Levels of Risk-tolerance**
**Description:** This figure presents the solution to the life-cycle outlined in Section 3. The model is solved using survey-elicited subjective survival beliefs.

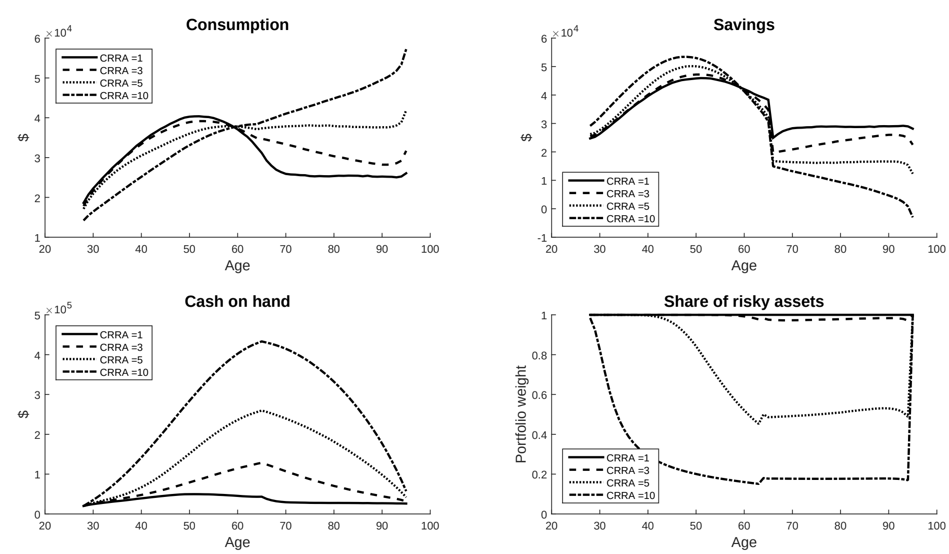


Figure A.3: **Subjective Survival Beliefs and Bequests**

**Description:** This figure presents the solution to the life-cycle outlined in Section 3. The model is solved using survey-elicited subjective survival beliefs. The model includes a bequest motive when Bequest = 1.

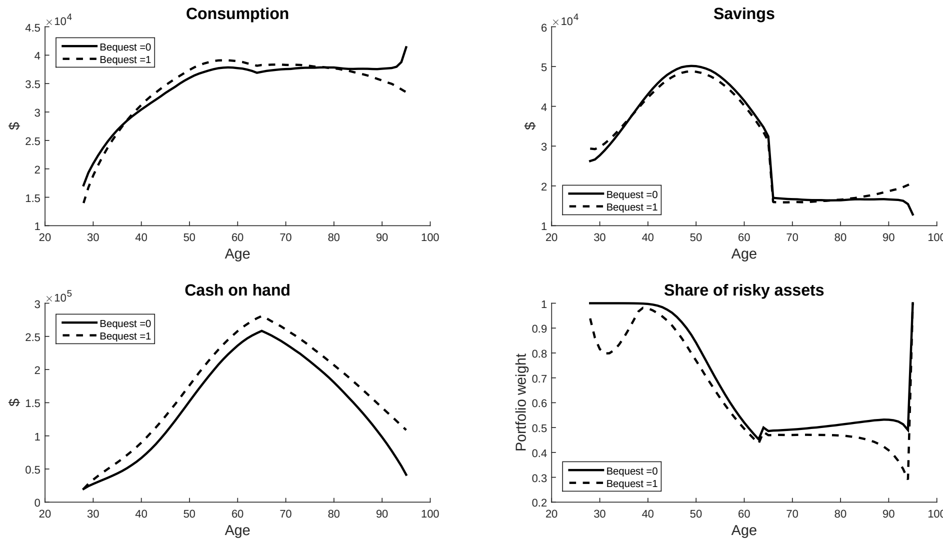
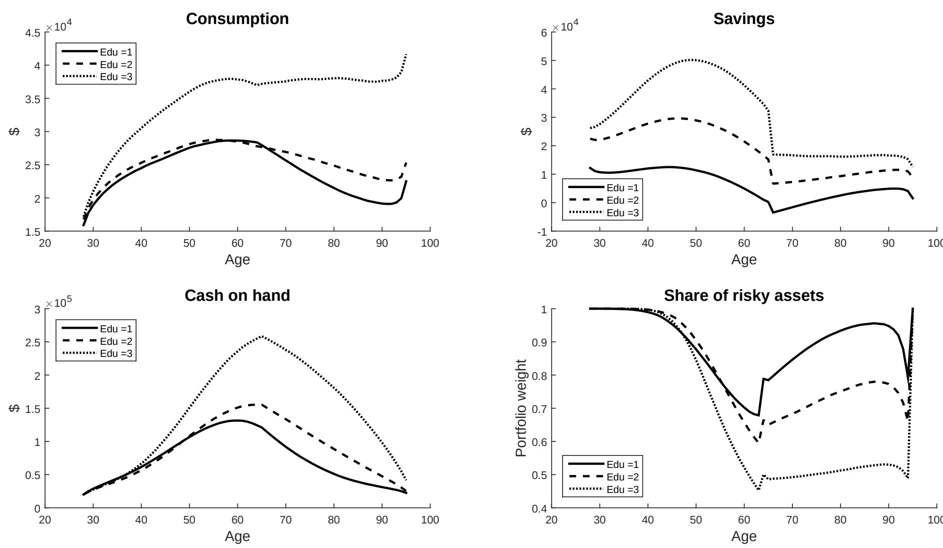



Figure A.4: **Subjective Survival Beliefs and Different Levels of Education**

**Description:** This figure presents the solution to the life-cycle outlined in Section 3. The model is solved using survey-elicited subjective survival beliefs. Education 1, 2, and 3 is no degree, high-school, and college graduate, respectively.



## A3: A Three-Period Overlapping Generations Problem with Safe and Risky Assets

The model's setup and assumptions are described in Section 4. The consumer's problem is:

$$\max_{b_t^y, e_t^y, b_{t+1}^r, e_{t+1}^r} \quad \{u(w_t^y - q_t^b b_t^y - q_t^e e_t^y) + \beta^y \mathbb{E}\left[u(w_{t+1}^r + (q_{t+1}^b + g)b_t^y + (q_{t+1}^e + d)e_t^y - q_{t+1}^b b_{t+1}^r - q_{t+1}^e e_{t+1}^r)\right]$$
$$+\beta^y \beta^r \mathbb{E}\left[u((q_{t+2}^b + g)b_{t+1}^r + (q_{t+2}^e + d)e_{t+1}^r)\right] \qquad \}.$$

His first-order conditions are:

$$\begin{aligned}
[b_t^y]: &\quad u_c(c_t^y)(-q_t^b) + \beta^y \mathbb{E}[u_c(c_{t+1}^r)(q_{t+1}^b + g)] &= 0\\
[b_{t+1}^r]: &\quad \beta^y \mathbb{E}[u_c(c_{t+1}^r)(-q_{t+1}^b)] + \beta^y \beta^r \mathbb{E}[u_c(c_{t+2}^o)(q_{t+2}^b + g)] &= 0\\
[e_t^y]: &\quad u_c(c_t^y)(-q_t^e) + \beta^y \mathbb{E}[u_c(c_{t+1}^r)(q_{t+1}^e + d)] &= 0\\
[e_{t+1}^r]: &\quad \beta^y \mathbb{E}[u_c(c_{t+1}^r)(-q_{t+1}^e)] + \beta^y \beta^r \mathbb{E}[u_c(c_{t+2}^o)(q_{t+2}^e + d)] &= 0.
\end{aligned}$$

### A2.1 Calibration

We parametrize our utility function as $u(c) = \frac{(c^{1-\sigma}-1)}{1-\sigma}$ for $\sigma = 2$, so that $u_c(c) = c^{-\sigma}$. We search over $\beta^y$, $\beta^r$ but to capture how consumers become relatively more patient as they age, we set them to be $(0.8, 0.99)$ to start with. We assume that wages and dividends follow the following distribution:

$$(w,d) = \begin{cases} (w^h, d^h) = () & Prob(w = w^h, d = d^h) = \\ (w^h, d^l) = () & Prob(w = w^h, d = d^l) = \\ (w^l, d^h) = () & Prob(w = w^l, d = d^h) = \\ (w^l, d^l) = () & Prob(w = w^l, d = d^l) = \end{cases}.$$

### A2.2 Non-linear system

The FOCs and the supply conditions imply a non-linear system of 6 equations and 6 unknowns for the steady state, given each state of the world (which is omitted in each of the following lines to avoid cluttering):

$$
\begin{aligned}
u_c(c_t^y)(-q_t^b) + \beta^y \mathbb{E}[u_c(c_{t+1}^r)(q_{t+1}^b + g)] &= 0 \\
\beta^y \mathbb{E}[u_c(c_{t+1}^r)(-q_{t+1}^b)] + \beta^y \beta^r \mathbb{E}[u_c(c_{t+2}^o)(q_{t+2}^b + g)] &= 0 \\
u_c(c_t^y)(-q_t^e) + \beta^y \mathbb{E}[u_c(c_{t+1}^r)(q_{t+1}^e + d)] &= 0 \\
\beta^y \mathbb{E}[u_c(c_{t+1}^r)(-q_{t+1}^e)] + \beta^y \beta^r \mathbb{E}[u_c(c_{t+2}^o)(q_{t+2}^e + d)] &= 0 \\
e_t^y + e_{t+1}^r &= 1 \\
b_t^y + b_{t+1}^r &= 1
\end{aligned}
$$

Or in terms of primitive variables (again, omitting state indices j):

$u_c(w_t^y - q_t^b b_t^y - q_t^e e_t^y)(-q_t^b) + \beta^y \mathbb{E}[u_c(w_{t+1}^r + q_{t+1}^b b_t^y + (q_{t+1}^e + d_{t+1})e_t^y - q_{t+1}^b b_{t+1}^r - q_{t+1}^e e_{t+1}^r) q_{t+1}^b] = 0$

$\beta^y \mathbb{E}[u_c(w_{t+1}^r + q_{t+1}^b b_t^y + (q_{t+1}^e + d_{t+1})e_t^y - q_{t+1}^b b_{t+1}^r - q_{t+1}^e e_{t+1}^r)(-q_{t+1}^b)] + \beta^y \beta^r \mathbb{E}[u_c(q_{t+2}^b b_{t+1}^r + (q_{t+2}^e + d_{t+2})e_{t+1}^r) q_{t+2}^b] = 0$

$u_c(w_t^y - q_t^b b_t^y - q_t^e e_t^y)(-q_t^e) + \beta^y \mathbb{E}[u_c(w_{t+1}^r + q_{t+1}^b b_t^y + (q_{t+1}^e + d_{t+1})e_t^y - q_{t+1}^b b_{t+1}^r - q_{t+1}^e e_{t+1}^r)(q_{t+1}^e + d_{t+1})] = 0$

$\beta^y \mathbb{E}[u_c(w_{t+1}^r + q_{t+1}^b b_t^y + (q_{t+1}^e + d_{t+1})e_t^y - q_{t+1}^b b_{t+1}^r - q_{t+1}^e e_{t+1}^r)(-q_{t+1}^e)] + \beta^y \beta^r \mathbb{E}[u_c(q_{t+2}^b b_{t+1}^r + (q_{t+2}^e + d_{t+2})e_{t+1}^r)(q_{t+2}^e + d_{t+2})] = 0$

$e_t^y + e_{t+1}^r = 1$

$b_t^y + b_{t+1}^r = 1$

The system gives us prices $\{q^b(j), q^e(j)\}_{j=1}^{j=4}$ in each state j, and bond and equity holdings $\{b^k(j), e^k(j)\}_{j=1}^{j=4}$ where $k \in (y, r)$, which implies consumption for each of the three generations.

Note that to solve the system, we can drop time subscripts because of symmetry (identical three generations are around in each cross section of time). That is, we solve a 6x4 fixed-point problem.

# Survey Description:

# YOLO: Mortality Beliefs and Household Finance Puzzles

Not intended for publication

## 1. Survey overview

The survey was administered on the Qualtrics Research Suite, and Qualtrics Panels provided the responses. Respondents were randomly assigned to treatments that, principally, varied (i) information provided and (ii) the questions posed. Following mortality judgments, participants were randomly assigned to one of three treatments in which they rated the risk factors considered in their own mortality judgments. Subsequently, participants reported judgments of inflation and financial preferences. They were then tested for financial literacy, and finally reported health status and other demographic information.

## 2. Sample

Invitations went out to residents of the U.S. Respondents were pre-screened for residence-status, English language fluency, and age. All respondents who failed to meet the screening criteria were discontinued from the survey. Only respondents who confirmed residence in the U.S., who professed English language fluency, and who reported to be of ages 28, 38, 48, 58, 68, and 78, were brought on to the survey proper. Upon meetings these criteria, we screened responses by removing any participants who took less than five minutes to complete the survey or had at least one gibberish response (e.g. sd#$2).

## 3. Mortality belief treatments

The treatments to which participants were randomly assigned depended on the participants' age. Participants of age $x = \{28, 38, 48, 58, 68, 78\}$ were randomly assigned to one of the following 21 treatments [4(information treatments) x 5(transition horizons) + 1(full life horizon)]:[7]

[7]For all information treatments (2, 3, and 4), respondents were asked to estimate their own expected longevity before reporting judgments of their transition probabilities. However, in the no-information treatments (1), respondents reported judgments of their transition probabilities before estimating their expected longevity. In both cases, each of the estimates was followed by a confidence judgment in the estimate (e.g., "How confident are you in the answer provided above?").

1. No information, questions about...

    (a) one-year transition horizon

    (b) two-year transition horizon

    (c) three-year transition horizon

    (d) five-year transition horizon

    (e) ten-year transition horizon

    (f) all transition horizons

2. Information about life expectancy for $y = \{30, 40, 50, 60, 70, 80\}$-year olds, questions about...

    (a) one-year transition horizon

    (b) two-year transition horizon

    (c) three-year transition horizon

    (d) five-year transition horizon

    (e) ten-year transition horizon

    (f) all transition horizons

3. Information about life expectancy and transition probability for $y$-year olds

    (a) one-year transition horizon

    (b) two-year transition horizon

    (c) three-year transition horizon

    (d) five-year transition horizon

    (e) ten-year transition horizon

(f) all transition horizons

4. Information about life expectancy and transition probability for $y$-year olds, plus reinterpretation of transition probability in terms of relative frequencies, and questions about…

   (a) one-year transition horizon

   (b) two-year transition horizon

   (c) three-year transition horizon

   (d) five-year transition horizon

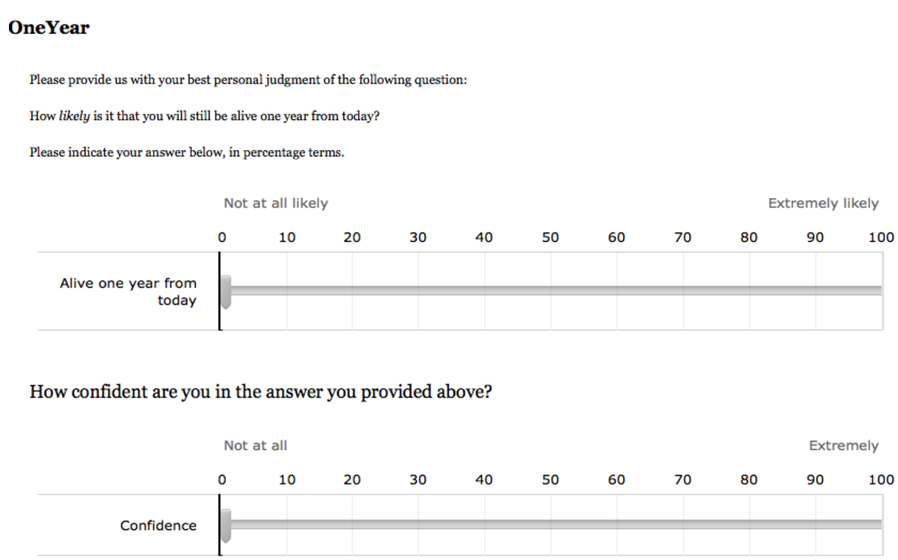
   (e) ten-year transition horizon

   (f) all transition horizons

5. Questions about plausibility of survival for entire life horizon (28-year olds only)

6. One question, mirroring the Health and Retirement Survey, asking participants about the likelihood that they reach 80 (90) for the 68-year (78-year) old sample

Questions on transition probabilities were given as follows:



## 4. Risk Factor Treatments

Participants were randomly assigned to one of three risk factor treatments. The risk factor treatments asked participants to indicate the relative weight placed on the risk factors in the prior mortality judgments. Common for all three conditions were the following risk-actors:

the natural course of life and ageing (“normal risk”)

medical conditions (e.g., cancer and heart disease)

dietary habits (e.g., unhealthy foods)

traffic accidents (e.g., car crash)

physical violence (e.g., murder)

a freak events (e.g., choking on your food)

In addition, each of the three treatments presented three risk factors of the same categories—natural disasters, animal attacks, and risky lifestyle—but with different examples, tailored to different regions of the United States:

West Coast

Natural disasters (e.g., earthquakes)

Animal attacks (e.g., shark attacks)

Risky lifestyle (e.g., scuba diving)

East Coast

Natural disasters (e.g., hurricanes)

Animal attacks (e.g., shark attacks)

Risky lifestyle (e.g., scuba diving)

Heartland

Natural disasters (e.g., tornados)

Animal attacks (e.g., bear attacks)

Risky lifestyle (e.g., skiing)

After each of the treatments, participants were asked to select one of two possible cognitive strategies that best described their prior mortality judgments. Participants had to pick one of the following three options:

1. I used analytic reasoning (e.g., “I might have considered background statistics or done some mental calculations”)

2. I used imagined scenarios (e.g,. “I imagined events that might happen to me”)

3. Other

Thereafter, participants were asked to produce their best numerical estimates for the following two rare events:

1. Annually, how many Americans are struck by lightning? (Please indicate a whole number.)

2. Annually, how many Americans are killed in plane crashes? (Please indicate a whole number.)