Mannheim Research Institute for the Economics of Aging

Bjarne Steffen

Formation and Updating of Subjective Life Expectancy: Evidence from Germany

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Bjarne Steffen[2]

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[2]The author can be reached at mail@bjarnesteffen.de

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Chapter 1

Subjective Life Expectancy Matters: Motivation and Definitions

As an input variable of individual decision-making, subjective life expectancy substantially influences economic decisions. Examples include old-age provision of the younger, dissaving of the older, and life-shortening behavior like smoking or self-induced obesity. This chapter evaluates the reasons to study subjective life expectancy from an economist's point of view and introduces basic concepts and definitions.

1.1 Reasons to Study Subjective Life Expectancy

Understanding subjective expectations is a fundamental step in the analysis of important economic decisions. The future is uncertain, and in many situations an objective probability distribution of future states of the world is unavailable or difficult to obtain. The situation of an unavailable objective probability distribution has been formalized by Savage (1954), who shows how individuals can base their decisions on a subjective probability distribution.

One of the major uncertainties all individuals are faced with is the length of their life. Even though reflection about the probability to die is unpleasant and rarely explicitly done[1], important decisions cannot be made without taking into consideration one's life expectancy, and inappropriate expectations can have grave consequences.

1.1.1 Decisions on Old-Age Provision

Most obvious, all decisions concerning life-cycle consumption and saving are affected by longevity expectations. Based on certain assumptions (rational individuals, diminishing marginal utility of consumption) and given a hump-shaped income distribution over lifetime, the *life-cycle model* derives paths of consumption, labor supply, and savings from the dynamic optimization problem over a horizon T (see Modigliani and Brumberg (1954)). Empirical evidence shows that extended versions of the pure life-cycle model describe many patterns of retirement savings reasonably well (see, e.g., Browning and

[1] People seem to follow what Greek philosopher Epicurus advised in his letter to Menoeceus: *"Accustom yourself to believe that death is nothing to us, for good and evil imply awareness, and death is the privation of all awareness; therefore a right understanding that death is nothing to us makes the mortality of life enjoyable, not by adding to life an unlimited time, but by taking away the yearning after immortality."*

Crossley (2001) for empirical evidence and Camerer and Loewenstein (2004) for limitations of the rational life-cycle model).

But what is the relevant horizon T? Empirical life-cycle-models either use the expected value of peoples' life expectancy ($T = \mathbb{E}[LE]$), or they implement an age-dependent probability to survive in every period such that $\sum s_t = \mathbb{E}[LE]$. However, studies show that people on average do not draw on actuarial mortality tables, but have a subjective survival curve which differs in several ways (see section 2.4.2). This seriously affects retirement saving decisions in younger years, a field of growing importance given the increasing necessity of private old-age provisions (such as *401(k)* plans in the U.S. or *Riester-Renten* in Germany). Understanding determinants of saving decisions is of professional interest for the life insurance and investment industry: Knowing the typical factors which lead people to estimate an especially high or low life expectancy can help to design and sell specific investment plans.

Besides the financial retail sector, policy makers, too, should care about subjective life expectancies: An adequate estimation is of high importance for individuals who suffer from sharp income cuts in the moment of retirement if they did not save enough. This also influences the economy as a whole, which is affected by a lower capital stock and higher expenses to support poor elderly persons.

For instance, a simulation study for Germany showed that underestimated longevity probability can explain why 60% of German households do not save sufficiently to cover the reduction in public pension income from the Riester reform act (Börsch-Supan, Essig, and Wilke (2005))[2]. Other decisions affected by subjective life expectatancies

[2] In recent years, the investments in private old-age provisions increased in Germany. See Börsch-Supan, Coppola, Essig, Eymann, and Schunk (2008) for a description of recent trends.

are the moment of retirement and the decision whether to annuitize wealth, which has been empirically analyzed for the U.S. (Hurd, Smith, and Zissimopoulos (2004)). It is an open question if systematic downward-biases in subjective life expectancies might also influence the public opinion concerning pension reforms increasing the retirement age.

1.1.2 Decisions on Lifestyle and Behavior

Besides savings, important decisions about unhealthy behavior are related to subjective life expectancy. One of the fastest growing public health problems in the United States is **obesity**, with 32.2% of adults being obese in 2004 (Ogden (2006)). In Europe the situation is worsening as well: Germany, for instance, counts about 32 mio. overweight people who risk to become obese (Bundesministerium für Gesundheit (2008)[3]). Even though severe health consequences of obesity are commonly known, economic research agrees that most of the overweight is caused by self-determined overeating and akinetic lifestyle (Bleich, Cutler, Murray, and Adams (2007)). Negative health consequences (including diabetes, cancer, cardiovascular disease and osteoarthritis) are illustrated by the resulting excess mortality. Do people underestimate excess mortality when they decide to stick to their unhealthy lifestyle? Empirical research using the Health and Retirement Survey found that misperception of negative consequences is actually widespread: While people with a very high body mass index (BMI) report slightly lower subjective longevity probabilities, the reductions are significantly less than those obtained from actuarial survival curves (Falba and Busch (2005)).

Another widespread unhealthy behavior is **smoking**. The negative health consequences provoked extensive discussions whether legisla-

[3] In June 2008, the German Federal Government launched an action plan "Deutschland In Form" increasing efforts to fight obesity.

tion has to put more effort into enlightening people of the danger, resulting in large warnings on tobacco packagings. In the European Union, these warnings include the remark "*smokers die younger*" (see Annex I of Art 5(2)(b), European Union (2001)). Indeed, longitudinal analyses indicate a reduction in life expectancy of 3 to 10 years depending on the intensity of smoking (Doll, Peto, Boreham, and Sutherland (2004)). Given the prevalence of smoking, the question whether this fact is correctly mirrored in subjective life expectancies is of large economic relevance. An empirical study using HRS (Health and Retirement Study) data found that smokers in general report lower subjective longevity probabilities than non-smokers, but no differences can be found between occasional and chain smokers (Smith, Taylor, Sloan, Johnson, and Desvousges (2001)).

Summarizing the facts above, people might keep unhealthy habits because they underestimate life-expectancy reductions from their behavior. Furthermore, another case of suboptimal decision-making occurs if people stick to unhealthy behavior because they (incorrectly) believe to have a short life expectancy anyway (e.g. because of genetic disposition). Evidence shows that people smoke more and tend to overeat if they have a short subjective life expectancy (Fang, Keane, Khwaja, Salm, and Silverman (2007)).

1.1.3 Understanding Human Behavior

Looking at the areas affected, an understanding of the formation and updating of subjective life expectancy contributes to precise modeling of economic decision making in a substantial way. This study summarizes what we know about subjective life expectancy, and provides new evidence using the German SAVE panel to split up longevity expectations and shed light on their determinants. To this extent, it adds a small piece to a better understanding of individual economic decision making.

1.2 Structure of the Study

The remainder of the study is organized as follows: After some basic definitions, chapter 2 summarizes past research on subjective life expectancy. While many important characteristics have been identified, some shortcomings of the literature become apparent and are elaborated in chapter 3: Most of the previous studies focus on the U.S. and results cannot necessarily be transfered to other countries; often only a partial analysis of single effects is done; and typically not subjective life expectancies but subjective survival probabilities are analyzed.

To contribute to these issues, empirical analyses are done in two steps: First, chapter 4 introduces the German SAVE dataset, which is used to identify basic patterns of subjective life expectancy in Germany. Multivariate analyses provide evidence about the relative importance of the determinants studied in various previous papers. A split-up of subjective life expectancy into estimated average life expectancy and individual relative expectations provides further insights. Second, chapter 5 presents a model for the updating of subjective life expectancy, suggesting that people apply a simple heuristic. The model is tested using the panel dimension of the SAVE data.

Finally, chapter 6 discusses implications and ideas for further research. Some sensitivity analyses as well as an excerpt of the SAVE questionnaire can be found in the appendix.

1.3 Definition of Basic Concepts

1.3.1 Measures of Remaining Life

As straightforward as *subjective life expectancy* sounds, a couple of different measures are commonly used, and definitions are not the same across studies. To clarify the discussion, the following terms are used in this study:

- **Remaining Life Expectancy (RLE)** is the "average number of years of life remaining to a group of persons reaching a certain age" (Nam (1994)).

$$\mathbb{E}\left[Remaining\,Years|Age\right] \tag{1.1}$$

  It decreases if a person gets older, for instance from 82 years at birth down to 4 years at an age of ninety.

- We define **Life Expectancy (LE)** as the sum of RLE and current age:

$$(LE\,|Age) = (RLE\,|Age) + Age \quad (1.2)$$

  Actuarial values are straightforward calculated using life tables. Subjective values can be obtained by surveys. However, people are not necessarily used to the concept of *expected values*. Consequently, people might answer a point estimation of the most probable age of demise instead (the *modus*). The typical phrasing of questionnaires (*"To what age do you expect to live?"*) is unclear whether it asks for the mean or the expected value. In actuarial data, the two statistics are quite different: The highest number of deaths occurs at the age of 84 for men and 89 for women, while the average life expectancy (at an age of 50 years) is 79 for men and 83 for women.

  In the literature, some authors use the term *"longevity expectancy"* in order to distinguish it from "life expectancy" which is solely used for RLE by these authors. In this study, the short form "LE" refers to life expectancy as described in equation (1.2). However, all statements are also true for RLE (as this is just LE less the current age).

- Naturally, a probability distribution (like the one for the moment of death) is not completely characterized by its mean). Consequently, **Survival Probabilities** are used besides LE to describe expectations. They can be described as point estimation of the probability to reach a specific age, for example "50%". Survival probabilities can be measured with survey questions (e.g., *"Using any number from 0 to 100 where 0 equals absolutely no chance and 100 equals absolutely certain, what do you think are the chances you will live to be 75 or more?"*). However it might be difficult for the respondents to think in probabilities (see section 2.4.1). The following notation is used: ${}_{20}p^s_{60}$ describes the probability to reach an age of 60 at a current age of 20, the superscript s refers to *subjective* probabilities (as compared to a for *actuarial* probabilities). If it is clear from the context at which age the respondents are asked, the notation is simplified to p^s_{60}.

- Theoretically, an inquiry of different survival probabilities can lead to a complete characterization of the probability distribution. One way to describe the distribution is the cumulative distribution function *cdf* of ages at death, giving a monotonic increasing curve. However, the convention is to use **Survival Curves**, a common concept in demography. Survival curves plot the probability of survival until different ages, leading to a monotonic decreasing curve. Figure 1.1 gives an example.

1.3.2 Actuarial and Subjective Life Expectancies

All the indicators presented above can be used to measure subjective as well as objective values. This study addresses subjective LE, as it is usually surveyed in interviews. For comparison we refer to *actuarial* LE at some points, which objectively projects from the actuarial age-specific survival rates as they can be found in life tables.

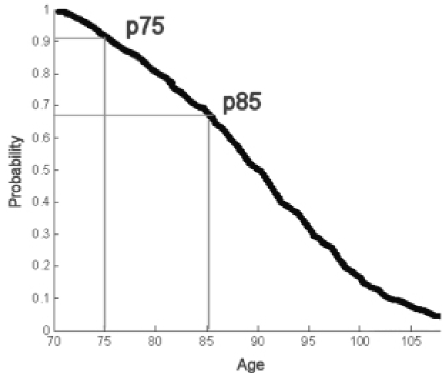

Figure 1.1: Example of survival curve

It should always be kept in mind that these numbers do not include expected improvements in LE in the future. Some models have been developed to account for the evolution of mortality rates, most prominently Lee and Carter (1992). The ongoing discussion among demographers concerning the "right" extrapolation shows that it is difficult to predict future technological trends[4]. To be able to make some statements nonetheless, Schnabel, Kistowski, and Vaupel (2005) as well as Börsch-Supan and Wilke (2007) extrapolate past mortality improvements linearly to estimate different scenarios for Germany.

Due to the high uncertainty of any extrapolation, this study follows the convention to use actuarial LE from life tables, and keeps in mind that these values underestimate "true actuarial" longevity and rather present a lower bound. At some points we will come back to this point, but for most purposes the approximation is reasonably good.

[4]See the articles and letters in *Science 02/2001* and *06/2001*.

Chapter 2

What We Know: Past Research

Given the relevance of subjective LE, a considerable amount of research has been pursued. It lies in the nature of the question that scientists from various fields have been active in this area, namely psychologists, sociologists, epidemiologists and economists. However, the literature seems quite separated; most researchers refer to previous work only from their own field. This chapter therefore tries to provide a synopsis of what we know so far. First, relevant work from psychology is described, followed by the presentation of two streams of sociological research. Subsequently evidence from epidemiology is presented. The emphasis finally lies on economic studies, discussing methodological questions, summarizing evaluations of subjective LE in representative samples, and giving an overview on theory and evidence of the process of updating these expectations. Finally, a collection in table form summarizes all evidence to serve as a handy overview for future research.

2.1 Psychology

Psychology defines its scope as the study of mental processes and behavior of humans (Gazzaniga and Heatherton (2003)). Hence it is natural that Psychological Science contributes to the understanding of subjective LE. In particular, *Scientific Psychology* identifies some typical heuristics which can help to understand the formation of subjective expectations in general. They are presented at a short glance. More specifically, *Applied Psychology* puts some effort into the understanding of subjective LE. While no cohesive theory for the formation of subjective LE has been developed so far, a couple of empirical studies address interpersonal differences.

2.1.1 Heuristics and Biases in Estimation of Probabilities

An important stream of psychological research explores the way how people estimate probabilities when required by a situation of uncertainty. The foundations are laid by Kahneman and Tversky (1973), Tversky and Kahneman (1974). Based on experimental data and survey responses, they develop a theory of probability estimations under uncertainty: Estimates are based on *heuristics*. While these heuristics sometimes yield reasonable estimates, they often cause biases. Most of the observed biases in probability estimation can be explained with two rules of thumb, namely the *availability heuristic* and the *representativeness heuristic* ((Reed (2004)).

Availability Heuristic

The availability heuristic postulates that humans estimate probabilities by taking into consideration the ease with which different realizations come to their mind. An alternative definition describes it as the *"over reliance on readily available, apparently relevant information in determining one's subjective beliefs"* (Tversky and Kahneman

(1974)). For example, it is possible that people estimate their LE by recalling the age at death of their acquaintances.

Slovic, Fischhoff, and Lichtenstein (1976) apply the availability heuristic to explore how people estimate the probability of 41 different causes of death (including diseases, natural hazards, accidents, and suicide). A sample of students conducted paired comparisons, resulting in strong evidence for the application of an availability heuristic, and especially underlining biases by media reports on certain death causes.

Representativeness Heuristic

The representativeness heuristic is relevant for the estimation of probabilities whether an event belongs to a certain category, or whether a realization is caused by some random process. A heuristic estimation is based on the extent to which the event is typical of the category/process, its representativeness (Kahneman and Tversky (1972)). The heuristic might be relevant for the formation of subjective LE, as the reliance on representativeness leads to a negligence of sample sizes and prior probabilities.

Relevance for Subjective LE

While the availability heuristic and the representativeness heuristic have been formulated for the estimation of probabilities in general, they certainly apply also to expectations concerning longevity. In consequence, the theory on heuristics under uncertainty has influenced both applied psychology and sociology (section 2.2.1).

2.1.2 Attitudes Toward Death

The relevant literature in applied psychology starts with research concerning the attitude toward death. Several studies reviewed in Lester

(1967) explore the relationship between the fear of death, personality and demographic variables. The findings have been contradictory, giving an inconclusive image of attitudes toward death. For instance, Middleton (1936) uses a survey among 825 students to show that college students *are totally unconcerned about death.* He asks questions like *"How frequently do you think about your death?"* in an anonymous questionnaire.

In contrast, Alexander, Colby, and Alderstein (1957) claim the concept of *death having the same importance to college students as sex and school.* To confirm their thesis, they perform an experiment in a group of 31 Princeton undergraduates (chosen to be representative, as they claim): An apparatus measuring the voltage between palm and dorsal as well as reaction times is used to distinguish the reaction to stimulus words related to different concepts.

The two studies exemplify the major problem of early research on attitudes toward death: The usage of a variety of measurement methods leads to researches actually assessing slightly different things. Some advances however have been made to standardize measures, like the *Collet-Lester Fear of Death Scale* (Lester (1990)). A recent collection of findings concerning subjective attitudes toward death is provided by Kastenbaum (2006).

2.1.3 Correlational Studies

A couple of studies explore subjective LE more specifically, focusing on the *"numerical estimate people make regarding their expected life spans"* (Robbins (1988b)), their subjective LE. All of these studies use surveys asking participants about their longevity expectations as well as other variables under study.

The first contribution has been made by Handal (1969), who uses a survey among 116 graduate students in an (untypically wide) age range of 20 to 64. He presents one of the first **comparisons of subjective and actuarial estimates** (taking the latter from US Bureau of the Census (1964)). The reported subjective LE is significantly overestimated for men, while this is not the case for women. This stems from the fact that there is no significant difference among subjective life expectancies of men and women, while actuarial LE differs by 6 years.

Handal's findings are widely cited within the psychological literature. It is important to note, however, that the comparisons have been done in a simplified way: He compares the mean of the subjective LE over all same-sex respondents with the actuarial LE of the mean age of the participants. Given the wide age range (with an equally wide range of actuarial LE), a simple comparison of means seems obscure. It cannot be said, for instance, whether the effect among men is caused by some very old or very young outliers, or whether the not-effect among women is caused because the biases of different age groups cancel out.

The general pattern was, however, confirmed by Tolor and Murphy (1967). Using a survey of 48 participants of a counselor training program (age span not provided), they also find men generally overestimating their life expectancies (unlike women). Interestingly, this is the case even though they tend to be accurate in their estimation of average life expectancies for men. The results are also replicated by Joubert (1992) (using a sample of 225 students).

As an explanation, Handal as well as Tolor and Murphy suggest that "subjective life expectancy" is differently interpreted by men and women. *"For women, [subjective LE] appears to be a critical indicator of attitudes toward death, whereas for men, it appears to be a manifestation of a defensive attitude toward death"* (Handal (1969)).

Some other correlates of LE have been examined. In a second step, Handal (1969) tests the **correlation of death anxiety and subjective LE**, using a standard *Affective Adjective Check List of Anxiety* (developed by Zuckerman (1960)) in the sample described above. For women he finds a negative correlation of death anxiety and subjective LE, even when "general anxiety" is partialed out. For men, no significant correlation is found. Joubert (1992) also uses his sample to test another relation, the **role of happiness**. Using a nine-point Lickert scale, he asks participants to rate their present happiness. Again, there is a significant positive correlation between happiness and subjective LE for women, but not for men. Teahan and Kastenbaum (1970) study the **correlation of unemployment and subjective LE**, using a sample of 29 men participating in a rehabilitation program (age range 21-44, all Afro-Americans). They find that self-estimated longevity is significantly lower for hard-core unemployed (which is defined as having had no single job for longer than three month during the last two years).

Several studies examine the **subjective LE as a correlate of family LE**. Robbins (1988a) asked a sample of 18 female undergraduates to report their subjective LE, as well as a subjective estimate of the "rough length of life" in their family, and the ages at death of parents, grandparents and siblings. She finds a correlation of 47% between subjective LE and the average family age at death, as well as a correlation of 77% between subjective LE and subjective "rough family length of life". This leads her to conclude that respondents are sophisticated insofar as they base their individual estimates on the parents' death rate, which she claims is more precise than taking the national average because mortality is correlated within families. Unfortunately no attempt is made to compare the validity of the alternative estimator.

In a follow-up study, Robbins (1988b) uses a larger sample including male participants (in total 86 undergraduates). The correlations reported are 26% for average family age at death and 68% for the subjective “family rough length of life”. Additionally, the analysis goes beyond the first study in two aspects. First, the correlation between subjective LE and the average family age at death is higher (35%) when the latter is corrected for “nonnatural causes” of death (not further specified). Second, a multivariate regression shows that subjective LE is best predicted by subjective family LE (no correction for endogeneity is attempted).

Finally, the **effect of premature parental death** has been examined. In a survey, 36 college students with at least one parent who died prematurely have been compared to 36 matched participants (Denes-Raj and Ehrlichman (1991)). Those who lost a parent prematurely reported a lower subjective LE than the control group.

2.1.4 Summary of Empirical Evidence

Looking at the empirical evidence from applied psychology, it can be said that a variety of correlates have been examined. The pertinence of these correlates is manifested, as well as the differences between men and women. However, the presented studies are characterized by two caveats: First, their datasets are very small, sometimes not bigger than a small class of undergrads. The composition of mostly psychology students as well as the prevalence of Caucasians, women or other groups delivers non-representative samples and allows quantitative propositions only for the studied group itself.

Second, most of the studies examine correlations one after the other and perform t-tests whether these are significantly different from zero, but do not conduct multivariate regressions. So, unfortunately, the available data is not exhausted, as it might be interesting to look at the interaction of different correlates as well.

Taking all this into consideration, applied psychology provides a basis of qualitative information on subjective LE. To make quantitative propositions, however, it is essential to use larger, representative datasets and employ methods from empirical social research.

2.2 Sociology

Sociology is the systematic study of the society, patterns of social relationships, social interaction, and culture (Calhoun (2002)), so the formation of subjective LE is seen in the environment of social relationships and culture. Analogously to psychology, the literature can be divided into *(1)* theoretical articles related to subjective risk perception in general and *(2)* empirical studies addressing subjective LE directly.

2.2.1 Theory on Individual Risk Perception

A constructivist stream of literature analyzes individual risk perception. In the context of policy decisions requiring the aggregation of individual risk perceptions, sociological research tries to explore the determinants of individual risk; given the empirical fact that perceived risk does not necessarily coincide with objective risk (the literature distinguishes subjective and objective risk as *"individual risk concept"* and *"classical risk concept"*, respectively). *"The risks that kill you are not necessarily the risks that anger and frighten you"* (Sandman (1987)).

Main insights of this research can be summarized as follows: Individual risk perception is a function of cognitive and motivational systems (as explored in psychology), but especially of the social, political and cultural environment. Sociologists recognize three **major characteristics of the environment influencing risk perception**: Voluntariness, Controllability and Responsibility, as well as the direction of influence. They can quickly be described using examples: ***(1) Voluntariness***: The subjective risk to suffer from accidents is higher if the risk stems from involuntary risks (like the risk to be killed from a military low-level flight over a densely populated neighborhood) than risks stemming from voluntary activities (like getting on board of a plane for a private flight) (Luhmann (1993)). ***(2) Controllability***: Individuals underestimate risks as soon as they have an influence on it due to overconfidence, causing an effect labeled "unrealistic optimism". E.g., most people think to be above average concerning driving skills, and underestimate the risk of fatal car accidents. (Weinstein (1984)). ***(3) Responsibility***: Natural risks are underweighted compared to man-made risks (e.g. the risk of earthquakes contrary to the risk of pesticides). Overviews by Jungermann and Slovic (1993) and Douglas and Wildavsky (1983) provide further information about this literature.

Relevance for Subjective LE

The whole stream of literature has in common that the subjective risk of single events is evaluated, each of which might end one's life. LE (as well as survival probabilities) can be interpreted as the aggregation of the risks of all thinkable events which could finish the life earlier. For instance, the probability to survive the next year could be split up as

$$P_{survive} = \prod (1 - P_{o_x} P_{k_x}) \tag{2.1}$$

where P_{o_x} is the probability that a certain event x (heart attack, car accident, nuclear meltdown) happens, and P_{k_x} is the probability that one is killed in that event (assuming that probabilities of different events are independent). Insofar, knowledge about psychological and sociological biases in the perception of P_o and P_k can help to understand biases in the aggregate.

One could hypothesize that in today's industrialized society most risks to die early are non-voluntary and non controllable, leading people to rather overestimate these risks and hence underestimate their subjective survival probability and LE. One could also hypothesize that people especially prone to "voluntary" and "controllable" risk (for example pilots) should relatively overestimate their LE. However, an unknown number of different events can end life, and insofar it is hardly possible to formulate hypothesis which are testable (and hence scientific in a Popper sense).

The analysis of life expectancies cannot be done bottom-up - but the theory on individual risk perception can still give some insight which biases might occur, and plays a role comparable to the psychological theory described in section 2.1.1.

2.2.2 Subjective LE by Age and Sex

The sociologists Mirowsky and Ross choose a top-down approach to explore subjective LE empirically, without a specific theory of individual risk in mind. They are using the 1995 Aging, Status and Sense of Control Representative Survey (ASOC), a national telephone survey among 2000 Americans, most of them being older than 59. As starting point, Mirowsky (1999) evaluates whether subjective LE corresponds to actuarial estimates by age, sex and race. Using a two-stage sample selection framework to control for item nonresponse of LE, he tests various hypotheses using the following regression model:

$$d_{S-A} = \delta_S - \delta_A = a_0 + a_1 x_{male} + a_2 x_{black} + a_3 (age - 45) + u_{d_{S-A}} \tag{2.2}$$

where δ_S and δ_A are the subjective and the actuarial life expectancies and x_i are dummy variables. The actuarial expectancies are taken from standard life tables (US Bureau of the Census (1995)). Major results are the following: First, probit estimations of the sample selection model show that the probability to answer the question on subjective LE strongly decreases with age. Second, a broad congruity can be stated between actuarial and subjective LE (correlation of 0.79), mostly stemming from the fact that both subjective and actuarial LE are mainly driven by age. Third, subjective LE is higher than actuarial, on average about one year. The hypothesis that people take cohort mortality trends into account when estimating personal LE is however rejected. This idea would imply that the difference between subjective and actuarial LE should get smaller with growing age (as less lifetime is left for technological progress), but in contrast the difference increases with age (a_3 is positive). The author infers that *"younger respondents do not incorporate favorable mortality trends"* and *"people seem to get more optimistic with age"*. Fourth, Mirowsky finds what he calls sex and race anomalies, with men and Afro-Americans seriously overestimating their LE. Both these groups report approximately the same subjective LE as women and whites, even though actuarial LE are lower (about 5 years for men and about 7 years for blacks). Mirowsky finally discusses the findings and concludes that economists and policy makers should *not* expect the public to make informed decisions about things like old-age pension savings.

The analysis is an early example of a methodologically clean study, which uses a representative sample and corrects for sample selection biases. Insofar it is comparable to economic papers presented below, with the main difference that subjective LE is studied (instead of survival probabilities).

2.2.3 The Importance of Socioeconomic Status

Based on the same data, a subsequent study of Mirowsky and Ross (2000) tests whether Americans expect longer lives the higher their achieved socioeconomic status is. The authors hypothesize a causal influence on subjective LE by three aspects of a person's socioeconomic status: Education, employment/occupation and economic well-being. *Education* regulates the access to occupation, income and wealth, and is seen to influence subjective LE because of current health and confidence about meeting future needs. The survey measures education in years. Following the authors, *employment* affects expectations through the same channels as education (namely health condition and confidence of the future); both current employment and the occupation history play a role. The survey contains a number of dummy variables for the respondent's and the spouse's employment. In their analyses, Mirowsky and Ross include the following: Whether retired, disabled, in school, part-time employed, ever unemployed for over 6 months. In addition, a numerical prestige score is assigned based on the current job (following the system of Nakao, Hodge, and Treas (1990)). Finally, *economic well-being* is included by income and the current or recent presence of economic hardship, where economic hardship means a lack of money to pay fundamentals like daily bills, clothes, or the rent.

Additionally, Mirowsky and Ross include a number of other explanatory variables, including what they call "potential mediators" (Measures on objective and subjective health, health behavior and self-confidence) and "possible confounders" (the basic demographics age, sex and race they analyzed in the first study). Out of many results, the most important findings of the regression analysis are the following: Each additional year of education increases the predicted LE by about .7 years, and adults currently in school expect to live about 2.5 years longer than same-age adults in full-time jobs. People currently unable to work because of disabilities have a shorter LE of 3.3 years, and economic hardship strongly reduces subjective LE (On average by 4 years if the hardship is long-past and by 8 years for current hardship). The effects seem to work through both of the mediators health and self-confidence. All effects are smaller in a linear regression without adjustment for sample selection biases, but remain significant.

2.2.4 Social Support through Family Relationships

A third study using the ASOC survey studies whether family relationships increase subjective LE (Ross and Mirowsky (2002)). By family relationships they mean marital and child-parent relationships. These relationships are indeed worth being analyzed, as they are usually bonded by affection and mutual obligation, providing potential for informal social support (Umberson, Williams, and Shar (2000)). Using a regression model similar to the ones described above, Ross and Mirowsky find that having adult children and living parents increases subjective LE, while young children at home and marriage have no influence (exception: marriage has a small effect for older men). There is a strong correlation between subjective LE and the reported emotional support as well as informal health support.

The authors hypothesize three channels for the positive effect of family relationships: By creating assurance about the future, by reinforcing health habits, and by improving current health. These hypotheses are not formally tested, but an analysis of related variables shows that the first channel has the strongest impact: Projected security about the future seems to be crucial for the length of life a person expects.

2.2.5 Summary of Empirical Evidence

The research presented above contributes significantly to an understanding of subjective LE: A general correlation between actuarial and subjective LE is found, but at the same time severe biases concerning the relative LE of men and Afro-Americans occur. Various measures of an individual's socioeconomic situation underline the importance of economic status, and family relations play a role by providing social support. All these determinants have been studied using the same dataset. Insofar additional outside evidence is strongly required. However the findings are a good starting point for further research.

2.3 Epidemiology

Epidemiology studies the health and illness of populations and the factors affecting it (Rothman (2002)). One typical measure of health is LE, and many studies examine possible predictors. Typically, *"subjective"* measures are phrased as *"self-rating"* in epidemiological terminology.

2.3.1 General Self-Ratings as Predictors of Mortality

An extensive literature demonstrates that self-ratings of health predict mortality, even after controlling for objective health measures, health habits, and sociodemographic characteristics. For an overview see Strawbridge and Wallhagen (1999).

2.3.2 Subjective LE as Predictor of Mortality

The first contribution including specifically subjective LE in addition to self-ratings of health is Van Doorn and Kasl (1998). Using a community sample of 1468 respondents of the Australian Longitudinal Study of Ageing (ALSA) and performing a logit regression whether people are dead in the second wave, they find that subjective LE predicts mortality, even when subjective health is included. The effect is stronger for men than for women. Their main contribution is to have shown that subjective LE has an independent effect on actuarial LE, and is not just a proxy of subjective health. However, the non-representativeness of the sample is a major limitation.

Siegel, Bradley, and Kasl (2003) provide results on a representative basis, using the HRS and AHEAD surveys. AHEAD is a national representative survey among persons aged 70 or older. The stratified dataset contains 5262 respondents who are followed for two years

(1993-1995). The HRS contains respondents aged 51-61. 8975 respondents are followed for three years (detailed description of data sets in section 2.4.3). During the preparation of their dataset, Siegel et al. note that respondents eliminated due to missing answers of subjective LE are older, which is in line with Mirowsky (1999). They are also less educated, less likely to be white and less healthy.

A National Death Index tracker file provides information about the actuarial mortality of the sample. 9% of the men and 5% of the women in AHEAD died during the three years, compared to 4% and 2% in the younger HRS sample. To analyze the predictive power of subjective LE, a Cox proportional hazard model (Cox (1972)) is estimated with the hazard function:

$$h_i\,(t) = \; h_0\,(t) \exp\left\{ {}_1 x_{i1} + \ldots +_k x_{ik} \right\} \tag{2.3}$$

The hazard rate $h_i(t)$ gives the probability to live an additional day, conditional on having lived until t. Explanatory variables ${}_j x_{ij}$ include subjective LE, subjective health, objective health measures, health behaviors and sociodemographic variables.

Summarizing their findings, Siegel et al. find that subjective LE is a predictor of mortality: People who expect to live longer are less likely to die during the period under study. The risk ratio for the likelihood is significantly lower for a reasonable differential in the subjective LE (between 2% and 20%). The effect is stronger for men in the HRS sample but not in AHEAD. Including subjective health measures into the estimation, the effect of subjective LE remains statistically significant in AHEAD, but not in HRS. The authors conclude that subjective LE is a better estimator among older people.

2.3.3 Summary of Empirical Evidence

Epidemiological Research shows convincingly that individuals are in general qualified to estimate their LE (whether this is especially true for very old people should be subject to further research). While no propositions concerning systematic biases are made, it is clear that subjective measures of LE have some predictive power of actuarial mortality.

2.4 Economics

Given the relevance of subjective LE as well as the increasing availability of extensive datasets, a couple of economists deal with the topic. This section sketches the methodological debates those researchers carried out within the economists' community, as well as the methods employed and all relevant results.

2.4.1 Methodological Discussions

At first glance, it might surprise seeing economists measuring the formation of subjective LE, which could be interpreted as another example of *"Economic Imperialism"* (Lazear (2000)), economists occupying intellectual territory outside their own field. Maybe economists should just use the results of psychologists and sociologists to feed their life-cycle models? As Hamermesh (2004) put it: *"Our ability to push buttons in STATA, SAS, TSP, or whatever is not unique: Psychologists and sociologists are perfectly capable of doing that."* He sees the strength of economics in the *"extend to which we can bring economic theory"* into the game.

Economists exploring subjective LE do not explicitly justify their agenda, but there are clear reasons why economists should deal with subjective measures of LE or survival rates: Most importantly, a deeper knowledge of the patterns and systematic biases in the formation of expected longevity is crucial for life-cycle-models and other fields of economic analysis, as pointed out in chapter 1. Research from other fields does not provide this information sufficiently accurate. Therefore, the simple necessity of better estimations justifies research. Furthermore, looking at the *updating* of expectations (including life expectations), economic theory, too, enters the arena and contributes to the understanding, as demonstrated in the following.

Measurement of Expectations

Apart from the general question whether economists should deal with longevity expectations at all, a long debate occurred whether the characteristic to be the result of survey responses disqualifies subjective measures from economic relevance. The discussion emerged in Manski (2004), who summarizes the necessities and possibilities to measure expectations by asking for subjective probabilities. The possibility to measure expectations is fundamental for all research on subjective longevity expectations, no matter whether they are measured as survival probabilities or longevity expectations. Consequently this discussion is presented in some detail.

Manski's motivation to examine the measurement of expectations is the following: Many empirical studies aim to identify a utility function which embodies individuals' preferences using information about their choices. For instance, the classical revealed preferences analysis infers preferences of an individual by observing consumption bundles she chooses facing different budget constraints and relative prices (Samuelson (1938), Samuelson (1948)). If this information is not available (as it is usually the case in practice), a modified form of revealed preference analysis is still possible, if the decisions of a random sample of heterogeneous individuals (facing the same discrete choice problem) are known. Imposing assumptions about the population distribution of preferences, a probabilistic choice model can be estimated (McFadden (1974)). Most researchers would agree with the statement that *"it is better to rely on what people actually do, and not on what they say"*.

In the case of partial information, however, Manski (2004) argues that revealed preference analysis is meaningless without knowledge of the agents' underlying expectations. Revealed preference analysis is straightforward given full information. In realistic settings, however, decision makers are usually not sure about the outcomes of alternative actions (which is undoubtedly true for decisions involving the length of life). Individuals have to form subjective expectations. The probabilistic density function expressing these expectations together with the utility function expressing the underlying preferences can only jointly be identified. A particular set of choices can be consistent with various specifications of preferences and expectations; Manski (2002) shows this for a standard ultimatum game.

The conventional remedy is assuming *rational* expectations, with other words the subjective probability density being equal to the *objective*, true probability distribution of outcomes. This assumption may lead to severe biases. In the case of an ultimatum game, for instance, a researcher might conclude a strong preference for fairness from experimental observations, even though the participants have standard preferences maximizing own payoffs, but expect their counterpart to reject the offer if unequal payoffs are proposed. A labor economist might infer that high school students are unconcerned about future earnings during their decision whether to attend college, even though they are very concerned but succumb to biased expectations concerning returns of further education (Manski (1993)). These examples illustrate the caveats of the assumption of rational expectations in order to reveal preferences from individuals' choices.

Given the case that identification of subjective expectations is crucial to predict behavior based on revealed preference analysis, Manski (2004) discusses several ways to measure expectations directly, by addressing individuals in surveys. The first approach, *verbal questions to measure expectations*, is widely used by attitudinal researchers (e.g. *"How likely do you think it is that you will loose your job - very likely, fairly likely, not too likely, or not at all likely?"*). However, this type of questions suffers from the persistent problem that interpersonal comparisons are impossible (e.g., the interpretation of "fairly likely" may differ among individuals). The second and more promising approach is to ask explicitly for *probabilistic expectations*, to get an absolute numerical scale which is interpersonally comparable. This method has been used for a long time in cognitive psychology and recently as well in economics (even though a first application can already be found in Juster (1966)). (Example: *"What do you think is the percent chance that you will lose your job during the next 12 month?"*). Surveys using this type of questions include the Health ans Retirement Study (HRS), the Survey of Economic Expectations (SEE) and SAVE (a detailed description of these datasets follows).

Thinking in Probabilities

A problem specific to the study of subjective *probabilities* is that people are often not used to think in probabilities. A numerical probability is usually only dimly available, as people have not thought enough about it in the moment they are asked (Spetzler and Stael von Holstein (1975), Morgan and Henrion (1990)). In survey practice, some advances have been made concerning presentation and framing of these questions in order to achieve reasonable answers. For instance, the HRS survey includes a *"training question"* (concerning the probability that it rains tomorrow) before subjective probabilities are asked for, and the SAVE survey presents a graphical number ray (figure 2.1).

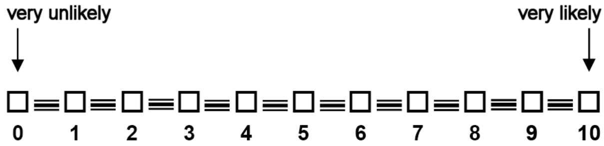

Figure 2.1: Example of probability visualization

These methods, however, do not remedy another problem, which is one of the central findings in prospect theory: People have problems especially with very high and very low probabilities, one of the characteristics of the *probability weighting function* which is empirically measured in *prospect theory* (Kahneman and Tversky (2000)).

Naturally, the problem of elicitation of probabilities does not affect the measurement of subjective LE (in years). This is a major advantage of studying subjective LE instead of subjective survival probabilities.

2.4.2 Consistency of Subjective and Actuarial Estimates

Economic research on subjective LE starts with Hamermesh (1985). Given the enormous rise of actuarial LE in the 20th century, he examines whether subjective LE incorporates these advances, and hence the common practice to use actuarial life expectancies in empirical studies testing life-cycle models is justified.

The analysis is based on a survey with two samples of (a) about 400 male economists and (b) about 450 randomly chosen individuals. The economists have been chosen because they are assumed to be familiar with probabilities. The random sample has been added to get an idea how the typical consumer might think (even though

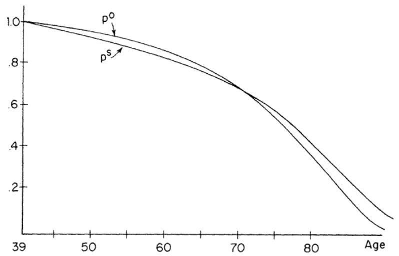

Figure 2.2: Subjective and Objective Survival Functions
Source: Hamermesh 1985

no representativeness is reached). Besides basic demographics, the questionnaire asks for subjective estimations of longevity, survival probabilities p^s_{60} and p^s_{80} as well as for parent mortality, smoking and exercise behavior. Results do not qualitatively differ between the two groups.

Hamermesh analyzes three types of consistency between subjective and actuarial LE. First, the **consistency in shape** of subjective survival distributions is examined. The survey contains questions regarding the subjective probability to reach an age of 60 and 80, respectively, and these values are used to fit a Weibull survival function (Figure 2.2). This subjective functions turns out to be flatter than the actuarial survival function, a result which is illustrated by direct comparison of $p^s_{60} - p^a_{60}$ and $p^s_{80} - p^a_{80}$: The respondents on average underestimate the probability to reach an age of 60, but overestimate the probability to reach an age of 80. This result is conform with the findings of Ludwig and Zimper (2007) who use the representative survey HRS; as well as the study of Betz (2005) (see below).

Second, Hamermesh examines **demographic and expectational consistency**. The hypotheses tested can be described with the following equation:

$$x + e_x^s = \beta_0 + \beta_1 \left(x + e_x^0\right) + \beta_2 DEL_x \tag{2.4}$$

where DEL_x is the predicted change in LE a person of age x can expect based on improvement in life tables during 1940-1980. He finds that the joint hypothesis of $\beta_0 = 0, \beta_1 = \beta_2 = 1$ describes the data better than any other hypothesis, and concludes that joint demographic and expectational consistency describe the respondents' LE quite well (meaning consistency with life tables while taking into account further improvements in longevity).

Third, **objective consistency** is addressed. Some questions concerning characteristics influencing LE have been included into the survey, and the coefficients of a simple regression on dummy variables describe the importance of this factors for individual LE. Two results are presented: On the one hand, the influence of personal behavior (specifically, smoking and regular exercises) is estimated consistently with actual influence. On the other hand, the influence of parents' and grandparents' longevity is largely overestimated.

Respondents with particular old or young relatives seem to base their own subjective LE much more on this information than evidence on genetic effects and non-genetic familial effects (from twin studies) suggest. This is in line with the availability heuristic described in section 2.1.1. Hamermesh summarizes that people do indeed extrapolate from actual life tables when they have to determine their individual LE, but with a subjective survival function being flatter than the actual distribution.

Börsch-Supan, Essig, and Wilke (2005) analyze the consistency of subjective and actuarial estimates of LE in Germany, using a small, representative subsample of the SAVE study (access panel with 487 observations). As described in more detail below (section 3.4), the survey asks respondents to estimate both the average LE for people of their age, and their individual subjective LE. Looking at the first measure, men overestimate the average LE by 1.4 years, while women state an estimated average LE which is 0.5 years lower than the actuarial value. However, actuarial values are taken from life tables, which do not incorporate technological progress. Consequently, subjective estimates should be well above actuarial LE. The authors conclude that respondents underestimate average LE.

The comparison is done by comparing mean LE over age, which reduces the explanatory power (section 2.1.3). In contrast, individual subjective LE is compared to actuarial values for five different age intervals. The basic pattern is the same, showing individuals underestimate their subjective LE. Insofar, the German data contradicts the findings for the U.S. The number of observations in the study is small (especially after being divided into different age intervals), hence an analysis with a larger sample is needed to make solid statements.

2.4.3 Survival Probabilities by Age, Sex and other Correlates

In empirical research, many economists study subjective survival probabilities (measured in percentage) instead of subjective LE (measured in years). One advantage of measuring longevity expectations in survival probabilities is that the results can be mapped directly into models of intertemporal decision-making, which usually require survival probabilities. Another advantage is the compatibility with Baysian updating models (see section 5) which are formulated in probabilities, not in years. Two major surveys, HRS and AHEAD, measure longevity expectations in survival probabilities, and a couple of papers use these data. The main drawback, however, is the difficulty people have to think in probabilities (section 2.4.1).

Subjective Survival Probabilities in the Age Group 50-61

The Health and Retirement Study (HRS) is a representative longitudinal survey data set, covering US-American households with the head of the household in the age of 51-61 during the first interview in 1992. It contains a question asking explicitly for subjective survival probabilities, which has been extensively analyzed. While the first wave asked all respondents to report p_{75}^s *and* p_{85}^s, subsequent waves ask only for one value, where the target age of interest $(80, 85, 90, 95, 100)$ is chosen to be about 11-15 years higher than the respondent's age (RAND (2008)).

Hurd and McGarry (1995) evaluate the first wave cross-sectional, to find out whether *(1)* the subjective probabilities behave like survival probabilities, if *(2)* their averages are close to actuarial averages, and whether they *(3)* correlate with other variables in a similar way as actuarial survival probabilities. Insofar the research question is pretty much the same as in Mirowsky (1999), with the main difference that subjective *probabilities* are evaluated, in contrast to subjective LE. Actuarial probabilities are taken from US Bureau of the Census (1993).

Their results show that in principle all these questions can be answered positively: *(1)* Talking about survival probabilities, for the same individual p_{85}^s should be smaller than p_{75}^s (**internal consistency**). Indeed, for 70.1% it is true that $p_{85}^s < p_{75}^s$, while only 2.5% report $p_{85}^s > p_{75}^s$. A surprisingly high share of people, however, report $p_{85}^s = p_{75}^s$, mostly bunching at 0%, 50% or 100% for both probabilities. However, Hurd and McGarry conclude that this inconsistency is tolerable. Addtionally, the basic pattern is confirmed by Elder (2007).

(2) In a **comparison with life tables**, they show that the average estimates of p_{75}^s are close to actuarial averages for men, while

women significantly underestimate it (0.66 and 0.75, respectively). Regarding survival to age 85, men report a higher subjective probability than actuarial survival, while that is not the case for women (table 2.1). The authors interpret this pattern as incorporation of future improvement of life expectancies. As the age of 85 is more distant than the age of 75, there is more time for technological advancements. However, this does not explain the gender differences.

HRS: Average Probabilities of Living to Age 75 or 85

	Men		Women	
	To 75	To 85	To 75	To 85
Subjective (HRS 1992)	0.62	0.39	0.66	0.46
Actuarial (1990 life table)	0.60	0.26	0.75	0.45

Table 2.1: Hurd, McGarry (1995)

(3) In a third step, Hurd and McGarry (1995) explore the correlation of subjective survival probabilities with socioeconomic variables, health conditions and behavior as well as family longevity (**external validation of variation**). They find the highest income quartile having a p^s_{75} which is 0.11 higher than the lowest quartile, besides similar variation in wealth and education. Smokers report a lower number, which is qualitatively in line with the actuarial situation. The highest correlation, however, can be found with perceived health. For instance, men reporting an excellent health report have a p^s_{75} which is 0.41 higher than for men in poor health. This finding confirms the evidence from Siegel, Bradley, and Kasl (2003) (see section 2.3.2).

In a final step, the authors combine the correlates in a linear regression. The coefficients of the mentioned variables have the expected sign; the inclusion of self-perceived health strongly reduces coefficients of other explanatory variables, but they remain significantly different from zero.

Subjective Survival Probabilities of the Older Old

In a subsequent study, Hurd, McFadden, and Gan (1998) evaluate subjective survival probabilities of the AHEAD survey, with participants significantly older than in the first HRS wave. Their main goal is to estimate survival curves and include them into a fairly complex life cycle-model; on their way they however present some facts which are in the scope of this study.

The survey of the Asset and Health Dynamics among the Oldest Old (AHEAD) is a representative biennial survey, covering US-Americans born in 1923 or earlier from 1993 on. Like the HRS (into which AHEAD has been merged later), a question asks for subjective survival probabilities. Again, the target age of interest $(80, 85, 90, 95, 100)$ is chosen to be about 11-15 years higher than the respondent's age.

AHEAD: Average Probabilities of Living to 85, 90, 95 or 100

	To 85	To 90	To 95	To 100
Subjective (AHEAD 1993)	0.51	0.38	0.31	0.29
Actuarial (1992 life table)	0.50	0.33	0.16	0.05

Table 2.2: Hurd, McFadden, Gan 1998

Table 2.2 presents a comparison of subjective and actuarial survival probabilities, arranged in a table similar to the HRS results (unfortunately no sex differences are reported). As in the HRS, the younger respondents (age 70-79) have average subjective survival probabilities close to the actuarial estimates. The older groups, however, show p^s much higher than p^a, with a growing overestimation in age.

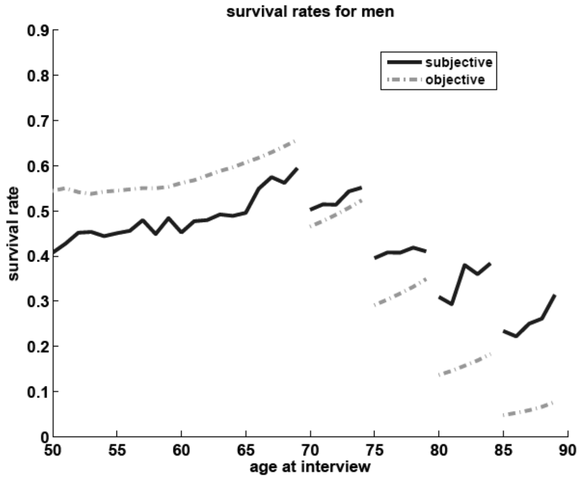

Figure 2.3: Survival Probabilities in HRS 2002-2004
Source: Ludwig, Zimper 2007

This pattern is confirmed by Ludwig and Zimper (2007). They analyze a pooled dataset of HRS consisting of the waves 2002-2004. In contrast to the sample of Hurd and McGarry (1995), the later waves contain a wider age range, as they follow the original participants as they get older. As mentioned, subjective survival probabilities are asked in a way comparable to AHEAD during the later HRS waves (different target ages). Figure 2.3 shows p^s and p^a for men of different ages. Ludwig and Zimper explain the pattern by growing optimism with age; a discussion is delayed to the section on updating LE (2.4.4).

Subjective Survival Probabilities in Europe

While most of the evidence cited so far is based on American HRS data, Betz (2005) uses the first wave of the Survey of Health, Ageing and Retirement in Europe (SHARE) to repeat the analysis of Hurd and McGarry (1995). SHARE is a cross-national survey of micro data on health and socio-economic status; the first wave has been conducted in 2004, including data from 10 countries from Scandinavia, Central Europe and the Mediterranean. The final dataset used by Betz (2005) contains $19,225$ observations (after deletion of item nonresponse and very old respondents). SHARE respondents are asked for the expected probability to survive until a target age chosen to be 10-15 years away. As only one target age is asked for, no check of internal consistency can be performed, and only step *(2)* and *(3)* of Hurd and McGarry (1995) are followed.

In a **comparison with life tables** from the respective countries, observations are pooled over countries in a first step. Table 2.3 presents key statistics in a way similar to the results above. The main finding, with younger people underestimating their survival probability to a lower target age, and older respondents overestimating the probability to survive to a higher target age, is confirmed. In a second step, the author discusses differences in subjective survival probabilities between countries. They seem to be small, which, however, might be due to the fact that observations are averaged over target ages and genders in the analysis.

SHARE: Average Probabilities of Living to Age 75 or 85

	Men		Women	
	To 75	To 85	To 75	To 85
Subjective (SHARE 2004)	0.69	0.55	0.70	0.54
Actuarial (various life tables)	0.70	0.43	0.83	0.58

Table 2.3: Betz (2005)

In addition, the **correlation of subjective survival probabilities with socioeconomic variables** is analyzed with cross-tabulations and regressions. In line with evidence from HRS, perceived health correlates negatively with subjective survival probabilities. In contrast, however, a *positive* correlation can be found between smoking and subjective probabilities for very high target ages. In sum, Betz (2005) concludes that the findings of Hurd and McGarry (1995) hold for European individuals.

Summary of Empirical Evidence

To summarize economists' findings on determinants of subjective estimates, one can say that while the "middle-age-group" estimates survival probabilities quite accurately (at least on average), older people (70 and beyond) increasingly overestimate their survival probabilities. The reason might be that people do not internalize that annual survival rates decrease with age. Differentiated by sex, men are relatively more optimistic than women according to life tables, which is in line with the sociological evidence on subjective LE.

2.4.4 Updating of Survival Probabilities

Besides analyzing the determinants of subjective longevity measures in cross-samples, an increasing economic literature analyzes the *updating* of subjective survival probabilities, hence the extent to which new information is incorporated into expectations. The new information under study are individual health shocks occurring to a person participating in a panel study. Most studies are based on HRS data; all papers on updating focus on subjective survival probabilities.

Foundations of Baysian Updating

Based on the *binomial probability model*, the theory of rational updating has been developed by Viscusi (1984), Viscusi (1985). He shows that a rational individual, applying Bayes' theorem to new information, will have a risk perception which is a linear function of his prior beliefs:

$$P_t = \left(\frac{\theta}{\theta+\gamma}\right) \cdot P_{t-1} + \left(\frac{\gamma}{\theta+\gamma}\right) \cdot S \tag{2.5}$$

where P_{t-1} are the prior subjective beliefs, $(\theta/(\theta+\gamma))$ the relative information of the prior, $(\gamma/(\theta+\gamma))$ the relative precision of the new information, and S is the risk equivalent of the new information.

Baysian Updating in HRS

Smith, Taylor, Sloan, Johnson, and Desvousges (2001) apply a Baysian updating model to evaluate how new information embodied in exogenous health shocks changes the longevity expectations of smokers and non-smokers. They find that smokers update their longevity expectations differently from non-smokers or ex-smokers. Especially if the health shock corresponds to smoking (e.g., lung cancer), they reduce their LE (measured as subjective probability to reach an age of 75) more dramatically than non-smokers.

Their sample includes 12,692 persons appearing in both the 1992 and 1994 wave of HRS. Two ways are chosen to analyze the differences in updating procedures among smokers, non-smokers and ex-smokers. First, two hypotheses are tested with *chi*-square tests: It can be maintained that smokers, former smokers, and non-smokers have different distributions of their subjective longevity probabilities in both waves. Additionally (and more interestingly), these groups adjust their longevity expectations differently if a health shock occurs among the two waves, which is shown using a *chi*-square analysis test for cross tabulations for smokers, non-smokers, and ex-smokers. Two different "health shocks" are taken into account: Serious health events which are smoking related and other serious health events. They find that current smokers only react to smoking-related shocks, while non-smokers update their longevity expectations after both types of shocks.

Several criteria are applied to use only "severe" health shocks, without presentation of rigorous arguments for the choice of the particular criteria. For instance, it is required that a person stayed at least 3 days in hospital between the waves (even though the survey question on hospital stays is not related to particular health events). Unfortunately, their analysis is not repeated including *all* health shocks which would provide an important sensitivity analysis.

Second, Smith et al. use a formal updating model in order to be able to control for other differences among the groups of smokers, former smokers and non-smokers. Various demographic control variables are included as well as a third type of health shocks: Worsening of activity limitations reported in the survey (e.g. climbing stairs). In the notation of equation (2.5), individual risk perception P_t is described as

$$P_t = \left(\frac{\theta}{\theta+\gamma}\right) \cdot P_{t-1} + \left(\frac{\gamma}{\theta+\gamma}\right) \times f(SS_{t-1}, GS_{t-1}, \Delta PC_t, \Delta AR_t, z_1, z_2 \ldots z_k) \tag{2.6}$$

where $f(\cdot)$ is the risk equivalent of the health shock (based on the smoking related health event SS_{t-1}, the general health event GS_{t-1}, the changes in existing conditions ΔPC_t and the changes in activity restrictions ΔAR_t). The structure of $f(\cdot)$ is assumed to be linear. Describing both the health shocks and the demographic controls as x_j, the model simplifies to

$$P_t = (\theta/\theta+\gamma)P_{t-1} + \alpha_0 + \sum_{j=1}^{k} \alpha_j x_j \tag{2.7}$$

Estimations support the hypothesis of smokers using a different updating rule than non-smokers, and motivate the authors to discuss several possible explanations for the differences which might be identified in focus group interviews. The main advance of the paper, however, is the development of a methodology to estimate an updating model from panel data.

Hurd and McGarry (2002) use the same HRS waves and confirm the finding that people do update their subjective survival probability when a negative health shock occurs, using a different model by regressing the difference in subjective survival probabilities between two waves on explanatory variables:

$$p_t^s - p_{t-1}^s = f(x\beta) \tag{2.8}$$

Out of a list of diseases, they find only newly diagnosed cancer to have a negative influence on subjective survival probabilities. Besides, also the death of a parent has a negative influence, especially if the demise occurs at a young age (under 75).

Baysian Updating and Medical Test Outcomes

One of the shortcomings the HRS data face is noise in the answers to the health questions. Liu, Tsou, and Hammitt (2007) exploit panel data from the National Health Insurance Program in Taiwan (NHI), which has detailed information based on a physical examination between the two waves. 620 participants of the voluntary examination at a Taipeh hospital answered both a survey before and after the examination in 2001. The authors test an updating model similar to equation (2.6), where $f(\cdot)$ contains (besides basic demographics) in different regressions *(1)* the number of abnormal test items in the examination, *(2)* the number of recommendations received from the doctors and *(3)* the number of health shocks. Health shocks have no significant influence in the data, while (1) and (2) reduce subjective survival probabilities. The authors interpret this outcome as support for the Baysian updating model.

Non-Baysian Updating

In a recent paper, Ludwig and Zimper (2007) extent the rational learning model by including psychological biases, leading to a *Non-*

Baysian Updating Model. Starting from the fact that people increasingly overestimate their subjective survival probabilities as they get older in the HRS data (Figure 2.3), they suggest a *"myside bias"* as explanation: Given the emotional content of death expectations, older people might have an optimistic bias in the interpretation of new information, leading them to ignore anything that makes a close death more likely. In contrast, young people might be more rational in their assessment, as their prospective demise is still far away and less emotionally loaded.

The learning model is based on Choquet Expected Utility (CEU) theory, which uses non-additive probability measures to account for ambiguity aversion. Optimism or pessimism are assumed to bias the updating process, by solving the ambiguity which arises given new information. In its parsimonious version, posterior beliefs of an individual of age j to survive until age m are

$$v_j\left(m|j\right) = \delta_j \lambda + \left(1-\delta_j\right) \tilde{\pi}_j\left(m|j\right) \tag{2.9}$$

with

$$\delta_j = \frac{\delta}{\delta + (1-\delta)\phi^j \pi(j)}\ , \quad \tilde{\pi}_j(m|j) = \left(\frac{\phi^m + \xi j}{\phi^j + \xi j}\right) \pi_j(m|j)\ , \quad \xi = \frac{\psi}{\alpha+\beta} \tag{2.10}$$

where the parameters are described as follows: ϕ as an initial bias in the additive estimator reflecting over- or underestimation, ξ as the strength of the rational Bayesian updating process, δ as measure for ambiguity and λ as the degree of optimism or pessimism by which an individual resolves his ambiguity.

Besides the theoretical modeling, the model is estimated using a pooled sample of the HRS waves 2000-2004. It explains 78% of the average variation in subjective beliefs for men and 96% for women (4%/7% of total variation in subjective beliefs). The authors compare the psychological bias model to a rational Baysian updating model, which is insignificant (all R^2 close to zero); they conclude that the rational updating model is violated in the data and the psychological learning model is a handy alternative to be used in life-cycle simulations.

Summary of Empirical Evidence

Summarizing the findings on updating models, the data indeed reflects Baysian behavior, with people reducing their subjective survival probabilities if they experience a negative health shock. Smokers seem to update in a different way than non-smokers, being excessively concerned about smoking-related health shocks. The age pattern of subjective survival probabilities can be explained quite accurately with an extended model allowing for psychological biases in the interpretation of health effects.

2.5 Summary: What we Know

Finding	Sample	Study
General Consistency (by Age, Sex)		
Subjective LE largely overestimated by younger men (ca. 6 years), because they do not account for actuarial difference to women	116 graduate students	Handal (1969)
	48 participants of counselor program	Tolor and Murphy (1967)
	225 students	Joubert (1992)
High positive correlation (79%) between subjective and actuarial LE	2000 US individuals (representative)	Mirowsky (1999)
Subjective LE slightly higher than actuarial, difference increases with age	2000 US individuals (representative)	Mirowsky (1999)
In Germany, subjective LE and estimated average LE lower than actuarial LE	487 German individuals from SAVE (representative)	Börsch-Supan, Essig, and Wilke (2005)
Subjective LE with predictive power for actuarial LE, besides objective and subjective health measures	1468 Australian individuals (non-representative)	Van Doorn and Kasl (1998)
	5262 (8975) US individuals from HRS (AHEAD) (representative)	Siegel, Bradley, and Kasl (2003)

Finding	Sample	Study
High "consistency in shape" (form of survival function), subjective survival function slightly flatter (underestimate p60s, overestimate p80s)	400 male economists, 450 randomly chosen US individuals	Hamermesh (1985)
"Internal consistency": p85s $<$ p75s for most individuals 50-61 years old	7946 US individuals from HRS (representative)	Hurd and McGarry (1995)
Men 50-61 years old estimate p75 consistently, overestimate p85	7946 US individuals from HRS (representative)	Hurd and McGarry (1995)
	19225 European individuals from SHARE (representative)	Betz (2005)
Women 50-61 years old underestimate p75, estimate p85 consistently	7946 US individuals from HRS (representative)	Hurd and McGarry (1995)
	19225 European individuals from SHARE (representative)	Betz (2005)
70-79 years old individuals estimate p85 consistently, overstimate p90, p95, p100. Overerstimation increases with target age	7393 US individuals from AHEAD (representative)	Hurd, McFadden, and Gan (1998)
Influence of Family		
Positive correlation (26-47%) of subjective LE with average family age at death	18 female undergrad students	Robbins (1988a)
	86 undergrad students	Robbins (1988b)
High positive correlation (68-77%)of subjective LE with "Rough family length of life" (estimation of family LE)	18 female undergrad students	Robbins (1988a)

Finding	Sample	Study
	86 undergrad students	Robbins (1988b)
Lower subjective LE if premature parental death occured	36 college students plus 36 matches	Denes-Raj and Ehrlichman (1991)
Influence of parents' and grandparents' longevity largely overestimated compared to actuarial data	400 male economists, 450 randomly chosen US individuals	Hamermesh (1985)
Living parents increase subjective LE	2000 US individuals (representative)	Ross and Mirowsky (2002)
Adult children increase subjective LE, no effect of young children at home	2000 US individuals (representative)	Ross and Mirowsky (2002)
No effect of marriage on subjective LE	2000 US individuals (representative)	Ross and Mirowsky (2002)
Positive correlation between subjective LE and reported emotional support by family members	2000 US individuals (representative)	Ross and Mirowsky (2002)
Influence of Education		
Subjective LE is lower for hardcore unemployed	29 men in rehab program	Teahan and Kastenbaum (1970)
Education increases subjective LE / subjective survival probabilities (1 additional year of education –> 0.7 years of subjective LE)	2000 US individuals (representative)	Mirowsky and Ross (2000)

Finding	Sample	Study
	7946 US individuals from HRS (representative)	Hurd and McGarry (1995)
Individuals in school with higher subjective LE (+2.5 years) compared to same-age full time-employees	2000 US individuals (representative)	Mirowsky and Ross (2000)
Economic hardship decreases subjective LE (4-8 years)	2000 US individuals (representative)	Mirowsky and Ross (2000)
Influence of Economic Situation		
High income correlates with high subjective survival probabilities (Highest income quartile: subjective survival probability +0.11)	7946 US individuals from HRS (representative)	Hurd and McGarry (1995)
Wealth correlates with high subjective survival probabilities	7946 US individuals from HRS (representative)	Hurd and McGarry (1995)
Influence of Lifestyle Behavior		
Subjective LE / subjective survival probabilities lower for smokers	400 male economists, 450 randomly chosen US individuals	Hamermesh (1985)
	7946 US individuals from HRS (representative)	Hurd and McGarry (1995)
Subjective LE higher for individuals regularly exercising	400 male economists, 450 randomly chosen US individuals	Hamermesh (1985)
Influence of Emotional Factors		
Negative correlation of subjective LE and death anxiety (only for women)	116 graduate students	Handal (1969)

Finding	Sample	Study
Positive correlation of subjective LE and happiness (only for women)	225 students	Joubert (1992)
Influence of Other Factors		
High positive correlation of subjective LE and perceived health	7946 US individuals from HRS (representative)	Hurd and McGarry (1995)
Blacks overestimate subjective LE (ca. 7 years)	2000 US individuals (representative)	Mirowsky (1999)
Updating of Subjective Survival Probabilities		
People reduce p75 if experiencing negative health shock	12692 panel respondents from HRS (representative)	Smith, Taylor, Sloan, Johnson, and Desvousges (2001)
	12692 panel respondents from HRS (representative)	Hurd and McGarry (2002)
	620 participants of Taipeh hospital examination	Liu, Tsou, and Hammitt (2007)
Smokers reduce p75 excessively if experiencing "smoking-related" health shock	12692 panel respondents from HRS (representative)	Smith, Taylor, Sloan, Johnson, and Desvousges (2001)
People reduce p75 if experiencing parental death	12692 panel respondents from HRS (representative)	Hurd and McGarry (2002)

Chapter 3

What we Want to Know: Contribution of the Study

The literature overview provided in the last chapter gives a picture of subjective LE, which is quite detailed in some regions and rather fuzzy in others. Several issues are addressed in the empirical part of the study, which introduces a split-up of subjective LE as a new analysis method.

3.1 Joint Analysis of Determinants

Many of the studies discussed above address one possible determinant of subjective LE, for instance unemployment, education or family situation. Especially the correlational studies do not take into account omitted variables and often interaction of different effects is unexplored.

The following analysis provides multivariate regressions including variables from all relevant groups of determinants and allows to single out the relative importance of influence factors. While we certainly still cannot answer all questions due to the limited number of variables in the available dataset, it is a step toward a more complete idea of the formation of subjective LE.

3.2 Analysis of Subjective LE in Germany

Most of the evidence in subjective LE refers to US data[1], which should not be surprising: With a GDP of about \$ 14 trillion per year, the United States are the world's most important economy, and with a population of 304 million also the largest country of the developed world. Many researchers are based at American universities, resulting in a traditional predominance of US-related studies in major scientific journals. In addition, the HRS provides superb data on subjective survival probabilities of Americans, which led to a wide use of these data.

However, it is not certain whether the measured perception of Americans can be taken as "general human behavior" and simply be transfered to other countries. Without a doubt, cultural differences between the US and for instance Germany are not trivial. In his in-

[1] Exceptions are Van Doorn and Kasl (1998)/Australia, Betz (2005)/Europe and Liu, Tsou, and Hammitt (2007)/Taiwan.

fluential work, Hofstede (2001) shows that despite all intra-national heterogeneity, countries differ significantly in various dimensions of culture, including *Uncertainty Avoidance* and *Long- vs. Short-Term Orientation*[2]. Consequently, there is no guarantee that German individuals exhibit the same patterns in subjective LE as American individuals. Additional evidence for the relevance of cross-country differences in subjective variables is provided by research on self-reported health (Jürges (2007)).

With the SAVE study, a comprehensive dataset is available for Germany, offering the opportunity to analyze subjective LE of the Germans. The following analyses provide evidence which can help German policy makers to react adequately to biases of subjective LE in their country.

3.3 Understanding Updating of Subjective LE

Past research provides some evidence on the updating of subjective survival probabilities if health shocks occur. Probabilities fit well into Baysian updating models, and the HRS dataset (providing large sample sizes) and the (very accurate) NHI dataset from Taiwan have been used to show significant updating effects. No study has yet investigated how different health shocks are reflected in the intuitive, easy-to-access measure of subjective LE (in years). This paper suggests a simple model of LE updating and tests it using the panel dimension of SAVE.

[2] Out of 53 countries, Germany ranks 29 in the Uncertainty Avoidance Index, while the United States rank 46. The Long-Term Orientation Index provides values for 23 countries, Germany ranks 14 and the United States 17.

3.4 Split-up of Subjective LE

The most innovative contribution of this study, though, is the introduction of a new method to analyze subjective LE: The breakdown of subjective LE into the individual perception how long people live *on average* (the **estimated average LE**), and the subjective expectancy how much shorter / longer an individual lives *compared to the average* (the **subjective LE compared to average**). While the first is influenced by the knowledge an individual has on actuarial life expectancies as well as the reference group an individual considers as "average", the second is a result of individual knowledge on personal longevity factors (like health situation etc.) and individual optimism / pessimism. Dividing subjective LE into these possible causes of biases helps to understand where biases stem from. This information can be used to decide how to address a certain incorrect pattern in subjective LE if policy makers want to improve individual decision making.

The SAVE survey includes several questions inquiring both dimensions of subjective LE. The comparison of these helps to understand the reasons for biases in subjective LE and provides an assessment of the rationality of updating procedures.

Chapter 4

Determinants of Subjective Life Expectancy: New Evidence from Germany

The empirical part of the study tries to answer the open issues summarized in the last chapter. This is achieved using data from the SAVE survey, which is pooled in a first step. This chapter describes the sample and available variables, as well as empirical models and estimation strategy. Descriptive statistics give an intuitive overview of LE in Germany, and numerous regressions provide evidence on the role particular determinants play in the formation of subjective LE.

4.1 Data and Variables

This section describes the dataset and variables used for the descriptive and inductive analyses in this chapter. The same data and variables also provide the basis for the analysis of updating behavior in the next chapter.

4.1.1 Pooled SAVE Sample

The SAVE study is a national representative survey of sociological, psychological, and financial characteristics of German households. Started in 2001, it has been conducted annually from 2005 on, surveying about 3000 households on a panel basis. SAVE is coordinated by the Mannheim Research Institute for the Economics of Aging (MEA), interviews are conducted by TNS Infratest. The shift to an annual cycle in 2005 also brought a major extension of the questionnaire, including detailed questions about the respondents' health status. The following paragraphs describe the preparation of the dataset.

Unit Nonresponse and Weighting

Following the convention, non-participation in the survey, despite being chosen by a random selection process, is called *unit nonresponse*, as opposed to *item nonresponse*, the refusal to answer a certain question within an otherwise completed questionnaire.

Participants of SAVE are chosen from a multiple stratified multistage random sample, including all German speaking households in Germany with a household head of eighteen years or older[1]. Participation in the study is voluntary, however various incentives together

[1] A small number of respondents has been selected on a quota basis during the experimental phase of the study and remained in the panel until 2006 (357 respondents in 2005, out of which 333 reappear in 2006).

with a special interviewer training are used to secure a high participation rate. Response rates vary between the years; 25%-50% refuse to take part in the study in every year (Schunk (2006), Börsch-Supan, Coppola, Essig, Eymann, and Schunk (2008)).

A unit nonresponse rate of around 50% might cause biases if the refusal occurs systematically. For instance, one might imagine high-income individuals to be especially time-constraint and hence denying participation more often than low-income individuals. In economic terms, they have a lower marginal utility of money (and hence a lower utility of the incentive offered for participation) and a lower utility of the "entertainment value" of the survey.

To reach representativeness, weights are calculated based on the Mikrozensus (a mandatory survey of the Federal Statistical Office of Germany). The following analysis uses weights based on income and age provided by MEA (Method 1 in Schunk (2006)). Weights are calculated as follows: Observations in SAVE are split into nine cells (3 age classes and 3 income classes), and the relative frequencies of these cells are compared to the relative frequencies of the respective cells in the Mikrozensus (from 2004, 2005 and 2006, respectively), giving 9 different weights for each year.

Weights are calculated for the whole dataset, for each year individually. In the analysis of this chapter, three years are pooled. However, many observations are from individuals who stay in the sample for all three waves, and the general structure of the sample does not change between the years. Hence each year's weights can be used for the respective observations. In the preparation of our dataset, some observations are deleted, e.g. because of missing values (see below). Because of this, weights do no longer exactly fit to get representative results from regression analyses. Still, as the number of missing values is very low, a bias in the results is very unlikely.

Besides theses points, the literature in applied econometrics discusses whether the use of sampling weights is inappropriate in general (Winship and Radbill (1994)). To be sure that our results are not driven by weighting issues, the regressions are also repeated *unweighted*. Respective results are reported in the appendix.

Item Nonresponse and Imputation

A couple of reasons may cause item nonresponse, including privacy concerns and cognitive barriers. This has to be taken into account, as effects might be over- or understated if item nonresponse is not random, but differs between groups like income quintiles or age classes. The phenomenon has been analyzed beginning with the research of Ferber (1966). Beatty and Herrmann (2002) provide an overview of the literature. For the SAVE survey, Essig and Winter (2003) analyze nonresponse patterns for certain variables (but not subjective LE).

Most of the missing values in SAVE occur in financial variables (income, savings, wealth). Unlike those variables, the sociodemographic and psychological variables used in the following analysis are easy to understand and do not raise considerable privacy concerns. Insofar, the response rates are high (see below), and biases in the estimates are not very likely.

One way to address item nonresponse is the imputation of missing values. The main advantage of the work with imputed datasets is the simplicity of application: A researcher can simply use the dataset as if item nonresponse would not exist. For SAVE, an iterative multiple imputation procedure has been used to impute missing values. In a first step, the conditional distribution of missing variables is estimated using regression methods on a sample with complete data. The conditioning on as many variables as possible preserves the multivariate correlation structure of the data. In a second step, a Markov-Chain Monte-Carlo method is used to replace the missing answers in the full data set by multiple draws from the estimated conditional distribution (Schunk (2008)).

Due to the stochastic nature of the imputation procedure, five different datasets are calculated for the imputation of every wave. Rubin (1987) presents a procedure how to average regression results in these datasets and modify standard errors of estimations to reach results comparable to an analysis of single datasets. The procedure (sometimes referred to as *"Rubin's Rules"*) is implemented in standard software packages (see Schafer and Olsen (1998) for an overview and Carlin, Li, Greenwood, and Coffey (2003) for a STATA package).

A shortcoming of Rubin's Rule is the high amount of required computations, especially if several independently imputed waves are combined and maximum likelihood estimators are used (as in this study). The alternative is to use single datasets and perform sensitivity analyses with other outcomes of the imputation procedure (Rubin (1987)). In this paper, each year's dataset No. 1 is used for all the results stated below. Tests repeated the analysis with combinations of other datasets, leading the same results.

A remaining caveat is the dependent variable: Using imputed variables on the left hand side (LHS) of a regression could bias estimators, as missing values in the LHS variable are imputed using basic demographic variables, who also show up on the right hand side (RHS). Consequently, a regression analysis would estimate a correlation structure between the LHS and the RHS variables which has been partly created during the imputation procedure. Due to the complexity of the imputation procedure, a correction of the estimations for imputed correlation is hardly possible.

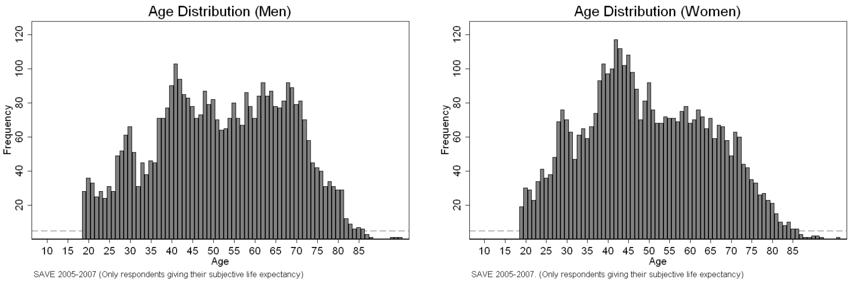

Figure 4.1: Age Distribution in SAVE 2005-2007 (unweighted)

Taking this into consideration, the following approach is pursued: For all independent variables imputed values are used where item nonresponse occurred, in order to use the whole available correlation structure and do not incur the risk of biases due to systematic nonresponse. For the dependent variables, namely the different measures of subjective LE, only actually reported answers are used.

Pooled Sample

For our analysis, responses are pooled to form a dataset out of the SAVE waves $\{2005, 2006, 2007\}$, consisting of 8710 observations. Out of these, 728 have missing values so that their subjective LE cannot be determined, leaving 7982 observations (91%). Descriptive statistics for key variables show that the group of people answering the questions concerning subjective LE does not differ much from the group of all survey participants (see table 4.1, Step 1). The only difference is a lower age average of about one year, because older participants answer questions about subjective LE less often. This is in line with the literature (Mirowsky (1999), section 2.2.2).

Figure 4.1 exhibits the age distribution of SAVE respondents. From 19-86 years at least 5 observations are available for every age and sex. Much of the following analysis is done per age class, and reasonable conclusions require an adequate number of observations. Consequently, the following analysis is limited to the age interval $[19, 86]$ for both men and women (table 4.1, Step 2).

Finally, respondents reporting a subjective LE below their current age (as described in the next section) are deleted. This might cause biases, but the number of such illogical reported subjective LE is very low (62 observations, 0.7%). The resulting dataset shows almost the same demographic structure as before (table 4.1, Step 3; see also section 4.3.3).

Comparison of Characteristic Variables in Dataset Preparation

	Raw data	**Step 1**[a]	**Step 2**[b]	**Step 3**[c]
Observations	8710	7982	7964	7902
Male	49.1%	49.7%	49.7%	49.6%
Married	59.0%	59.6%	59.7%	59.7%
With children	77.5%	77.3%	77.3%	77.3%
With Abitur	27.3%	28.3%	28.3%	28.5%
Age[d]	51.6 (16.1)	50.7 (15.8)	50.7 (15.7)	50.5 (15.6)
Income (EUR)[d]	2312 (1841)	2331 (1835)	2332 (1835)	2334 (1829)

[a]Deleted if missing values for subjective LE
[b]Only age interval 19-86 years
[c]Deleted if subjective LE $<$ age
[d]Mean (Standard Deviation)

Table 4.1: Dataset Preparation

4.1.2 Variable Construction

Before presenting descriptive and inductive statistics, this subsection describes the construction of the dependent variable as well as the regressors. Some lines motivate the choice of these particular variables.

Measures of Subjective LE

In the SAVE study, subjective LE is surveyed in several steps. First, respondents are asked which age they think men and women of their age will reach on average (LE_{avr}). In a next step, the interviewer asks whether the respondent beliefs to live shorter, longer or about the same as average (C). Finally, he asks how many years the respondent believes to live shorter or longer than average (if this has been stated before) ($Years_i$, $i = {}_{shorter,longer}$)[2]. Together, these variables allow to calculate individual subjective LE (SLE_{ind}):

$$SLE_{ind} = LE_{avr} - \mathbb{1}\left(C = {}_{shorter}\right) \cdot Years_{shorter} + \mathbb{1}\left(C = {}_{longer}\right) \cdot Years_{longer} \tag{4.1}$$

In this study, the compound measure SLE_{ind} is analyzed besides the single variables LE_{avr} and C. Compared to the literature, the questions concerning SLE are non-standard, as they include a hint to use LE_{avr} as reference group for the determination of personal subjective LE. The over reliance on the average family length of life reported repeatedly in the literature might be reduced by this design (section 2.1.3). For our purposes - the analysis of a representative population sample - this does not matter, if anything it reduces noise and makes it easier to determine typical determinants of subjective LE[3].

The major advantage of the SAVE design is the additional information the dataset provides: We do not only know the subjective LE of the individuals, but also what they perceive as being the average LE and if they believe to live shorter or longer than the average (and how much). Insofar we can distinguish biases in estimated average LE and determinants of the individual relative LE (being a composition of private information and optimism/pessimism).

[2]The exact wording of the questions can be found in appendix B.

[3]Of course only determinants other than *over reliance on average family length of life* can be determined.

Independent Variables

To reveal the interaction of different determinants of subjective LE, several groups of RHS variables are included into the regressions (following the structure of literature table. The use of particular variables is discussed briefly; available variables which are not included are mentioned as well.

- **General characteristics** include the respondents' age, sex, and region. Due to the actuarial gap of life expectancies between ***men and women***, as well as the structural difference between male and female biographies, all analyses are done separately for men and women. This divides the sample size in halves, but there is no alternative: Interaction terms between sex and all other determinants would have the same limiting consequence for the precision of estimators. Furthermore, independent analyses for men and women can be seen as additional sensitivity analyses.

  In regressions, the respondents' ***age*** is included as a linear and quadratic term. It is normalized around the sample mean (separately for men and women) to be able to interpret the signs of the respective coefficients. Additional non-linearities at critical ages (e.g., 65 years) have been checked for but could not be identified in any regression. Some age effects might also be captured by the dummy variable for "retired" (see below).

  The sample size does not allow an analysis on state level, because the subsamples are not representative for single Bundesländer. To allow at least for differences between Western and Eastern Germany, a dummy variable ***Eastern Germany*** is included into regressions.

- Past research showed that **family characteristics** play an important role in the formation of subjective LE. Dummy variables for ***marital status***, whether the respondent is ***widowed*** and the ***existence of children*** are included. The number of children living in the household or outside the household is insignificant (as well as various nonlinear specifications). Information on parental longevity is not available in the SAVE survey.

- Out of the available measures of **education**, dummy variables for passing at least the ***Abitur*** (German university entrance qualification) and for the completion of at least ***undergraduate studies at a college or university*** (German Fachhochschul- or Universitätsstudium) are included. Other qualifications are insignificant.

  To proxy how well-informed a person is, we tried to include the availability of an internet access and the frequency of using the internet. In most regressions the respective estimators have however been insignificant. Unfortunately, no adequate proxy is available for education-independent knowledge or expertise[4].

- One strength of the SAVE survey is detailed data concerning the participants' **economic situation**. The regression analysis includes ***household income*** in linear and quadratic specification, as well as a dummy whether the respondent is retired. Wealth variables are insignificant, probably due to noise in measurement of wealth (which includes items like claims from occupational pension plans which are difficult to specify).

  To examine the effect of ***unemployment***, two dummy variables are included. "Current unemployment" refers to the *present* situation, while "Unemployment history" measures whether a person has *ever* been unemployed for at least six months.

[4]Beginning in 2007, the SAVE survey contains a quiz part to measure *financial literacy*; the results might be used as soon as they are available for several years.

- The importance of **lifestyle and behavior** for actuarial LE makes it imperative to include these dimensions into the analysis of subjective LE. To measure the influence of ***smoking***, dummy variables for current smokers and former smokers are included, as well as dummies for the (at least) weekly ***consumption of alcohol*** and (at least) weekly ***exercise***. In addition a dummy measures whether participants do ***voluntary work*** on a regular basis.

- Given the particular importance the individual **health situation** has for subjective LE, variables have been carefully selected to describe the perceived health conditions. Particular diseases and disorders are too diverse to occur in a representative way, so the information content is used only later in the analysis of updating (chapter 5). For this chapter, two dummy variables are used as summary measures: ***Bad health*** describes a respondent calling her health status as "bad" or "very bad" (1 or 2 on a 5-point scale). ***Long-term health problems*** contains the answer to a yes/no- question asking for chronic health problems. Naturally both variables can be true for one person.

Tables 4.2 and 4.3 provide an overview of all variables used.

Variable Definitions and Summary Statistics 1/2

Variable	Definition	Mean	Std.Dev.
Male	1 if person is male	.4956	.5000
Age (raw)	Respondent's age (years)	50.50	15.59
Age	Age standardized around *weighted* mean	4.179	15.57
Age squared	Standardized age squared	259.8	287.8
East	1 if lives in Eastern Germany	.2766	.4474
Married	1 if married and lives together with spouse	.5973	.4905
Widowed	1 if widowed	.0697	.2547
Children	1 if has at least 1 child	.7725	.4193
Practical help	1 if received practical assistance during last year	.4403	.4965
Highschool (Abitur)	1 if achieved education is Abitur or higher	.2848	.4513
College (Hochschule)	1 if completed university studies (incl. FH)	.1631	.3695
Income	Monthly household net income (in 1000 EUR)	2.339	1.828
Income squared	Income squared	8.789	37.747
Retired	1 if retired	8.789	37.747
Current unemployment	1 if is currently unemployed	.0909	.2876
Unemployment history	1 if ever been unemployed for 6 month or longer	.3190	.4661
Current Smoker	1 if smokes regularly	.2887	.4532
Ex-smoker	1 if is nonsmoker, but smoked regularly earlier	.2890	.4533
Weekly drinking	1 if consumes alcohol at least weekly	.2890	.4533
Voluntary work	1 if engages in the community voluntarily	.6415	.4796

Table 4.2: Overview Variables part 1

Variable Definitions and Summary Statistics 2/2

Variable	Definition	Mean	Std.Dev.
Bad health	1 ranks health status as bad or very bad	.0863	.2808
Long-term health problems	1 if reports long-term health problems	.4703	.4991
Estimated Avr LE (male)	Estimated average LE of age-group (years)	77.00	5.619
Estimated Avr LE (female)	Estimated average LE of age-group (years)	81.43	5.703
Expect LE longer	1 if expects to live longer than average	.1601	.3667
Expect LE not shorter	1 if expects to live longer or same as average	.8484	.3587
LE	Subjective LE (years)	79.18	8.005
Year effect 2005	1 if observation is from 2005	.2660	.4419
Year effect 2006	1 if observation is from 2006	.4014	.4902

Table 4.3: Overview Variables part 2

4.2 Descriptive Analysis

To answer the question what subjective LE *in Germany* looks like, some charts exhibit typical patterns and give an idea where biases stem from.

4.2.1 Personal LE Compared to Age Group

To start, figure 4.2 compares the means of subjective LE and estimated average LE by sex and age. If people on average do not over- or underestimate their relative LE compared to a same-sex age group, the two measures should be on average the same. This is indeed the case, with a correlation between SLE_{ind} and LE_{avr} of 0.736 and 0.745 for males and females, respectively.

The graph shows the development of $\overline{SLE_{ind}}$ and $\overline{LE_{avr}}$ as people get older. In line with the high correlation the measures follow closely. However, for the group of old men (from about 70 years on) and very old women (from 80 years on), the mean subjective LE lies well above the estimated average LE.

The high correlation between the means of individual subjective LE and expected average LE can in principle stem from two facts: Either most people believe to live about as long as the average. Or the individuals' relative LE deviate about the same in both directions and cancel out in the mean. Figure 4.3, plotting the combined distribution of $C_{shorter}$ and C_{longer}, shows that both effects play a role, but the first one is more important: 65.0% of male and 72.6% of female respondents expect to live about as long as average. This is surprisingly high, given the heterogeneity in personal health situation, socioeconomic status, family situation etc. Among men, 16.2% believe to live shorter, compared to 18.8% expecting to live longer. For women, the number of respondents expecting to live shorter is slightly higher than the number of those expecting to live longer

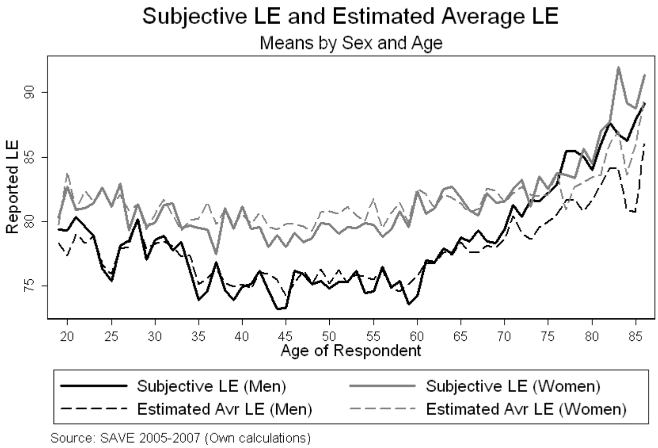

Figure 4.2: Estimations of LE in SAVE by Age

(14.1% and 13.2%, respectively).

Figure 4.4 supports an hypothesis which already arose from figure 4.2: The overhang of people expecting to live longer stems from the very old. Especially among men older than 75 and women older than 80, up to 50% believe to live longer than average, compared to almost 0% believing to life shorter. This is in line with the model of Ludwig and Zimper (2007), who hypothize that people become more optimistic as they get older. The pattern found here, however, could also be caused by sample selection effects or a misunderstanding of the question (section 4.3.3).

A natural question is *why* people believe to live shorter or longer than average. The SAVE survey asks for the reasons, offering four different explanations (multiple answers are possible). The distribution of the reasons can be found in figure 4.5. The main reason for an expected shorter life is by large a poor health status (64.0% for men

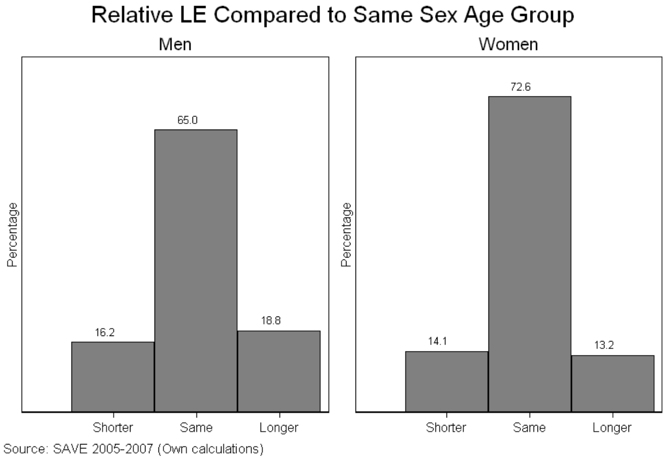

Figure 4.3: LE Compared to Average (unweighted)

and 65.2% for women). Among the people expecting a longer life, the offered reasons play about the same role. Interestingly, the length of life of close relatives is seen as influencing own LE about twice as often if the relatives reached a high age, compared to an early demise. Furthermore, a healthy way of life is named as reason by 68.0%/66.6% of those expecting a longer life, while only 18.0%/28.0% of those expecting a shorter life attribute this fact to an unhealthy way of life.

Summary

To summarize the key findings so far: More than two thirds of Germans believe to have about the same LE as their age group, with women believing to be average more than men. Among older people, the proportion of optimists believing to live longer than average increases strongly. Bad health conditions are seen as the main reason for a life shorter than average.

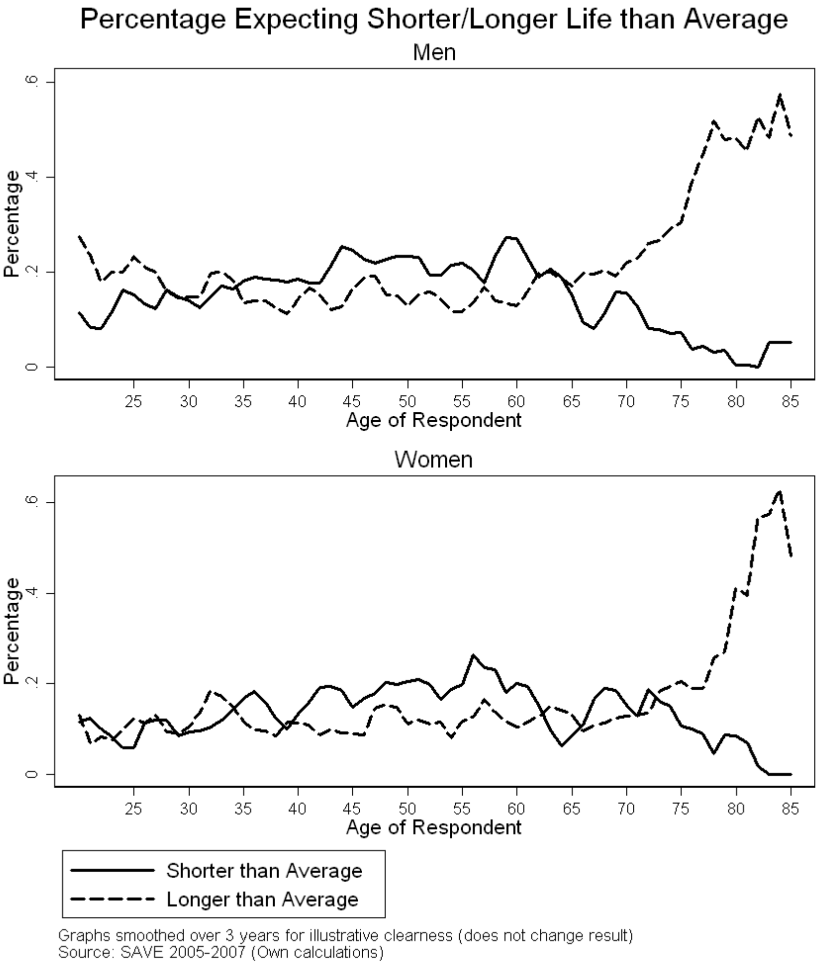

Figure 4.4: Comparison with Average at Different Ages

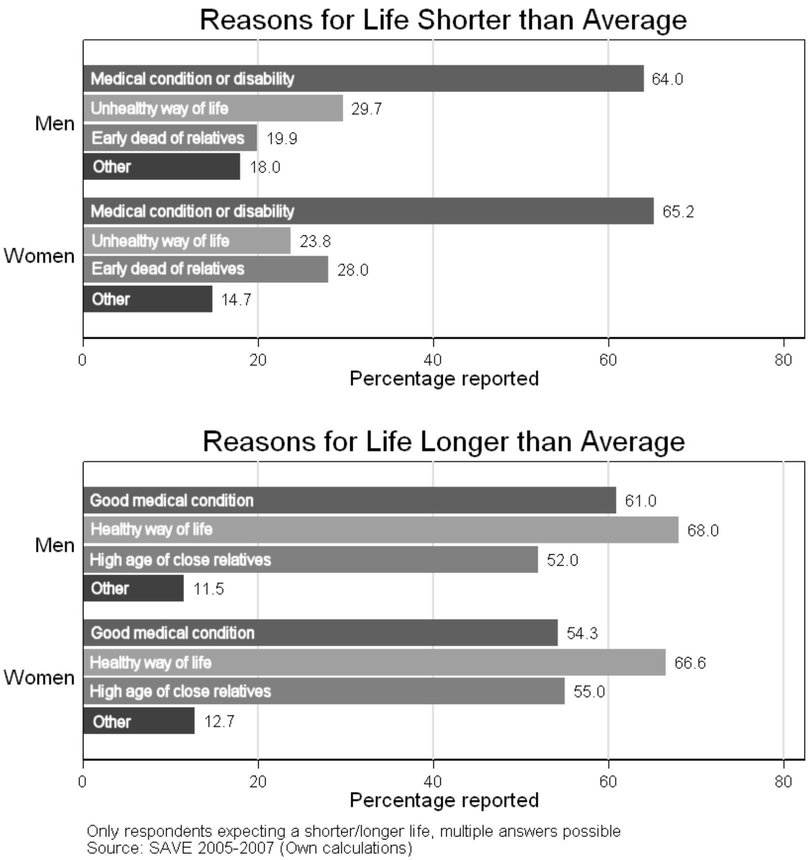

Figure 4.5: Reasons for Expected Shorter or Longer Life

4.2.2 Comparison of Subjective and Actuarial LE

A comparison of mean subjective LE with actuarial LE for a same-sex age group provides evidence on the accuracy of individual estimations and the direction of systematic biases. For comparison, actuarial data is taken from Statistisches Bundesamt (2007). A simplified confidence interval of subjective LE is calculated (assuming that the distribution of $\overline{SLE_{age\,j}}$ is reasonably well approximated by a normal distribution) as follows[5]:

$$\left\{\overline{SLE_{age\,j}} \pm 1.96\, SD(SLE_{age\,j})/\sqrt{n_{age\,j}}\right\} \tag{4.2}$$

Figure 4.6 shows that average subjective LE follows actuarial LE, which is also reflected in the correlation between mean subjective LE and actuarial LE of 85.9% for men / 84.3% for women. Considering the fact that actuarial LE is calculated from life tables that do not incorporate technical progress (see the discussion in section 1.3.2), individuals should slightly overestimate their subjective LE. In sharp contrast, the subjective LE curve lies *below* the actuarial curve, exhibiting both men and women on average significantly underestimating their subjective LE. This is true for a wide age rank, only the very young (below 35 - where actuarial LE is still low) and the very old (men older 75, women older 80) seem to be in the actuarial region.

This pattern of systematic underestimation contrasts the findings in past research with American data, stating that estimations of subjective LE are quite well on average and if anything slightly overestimated. Figure 4.7 provides a comparison of the German LE curves

[5]Unlike the regressions in the next section, the descriptive analysis provided here does not require a special treatment of standard errors due to the original panel structure of the pooled dataset. Confidence intervals are calculated for each group of same age respondents, and no individual appears twice in the data *having the same age*.

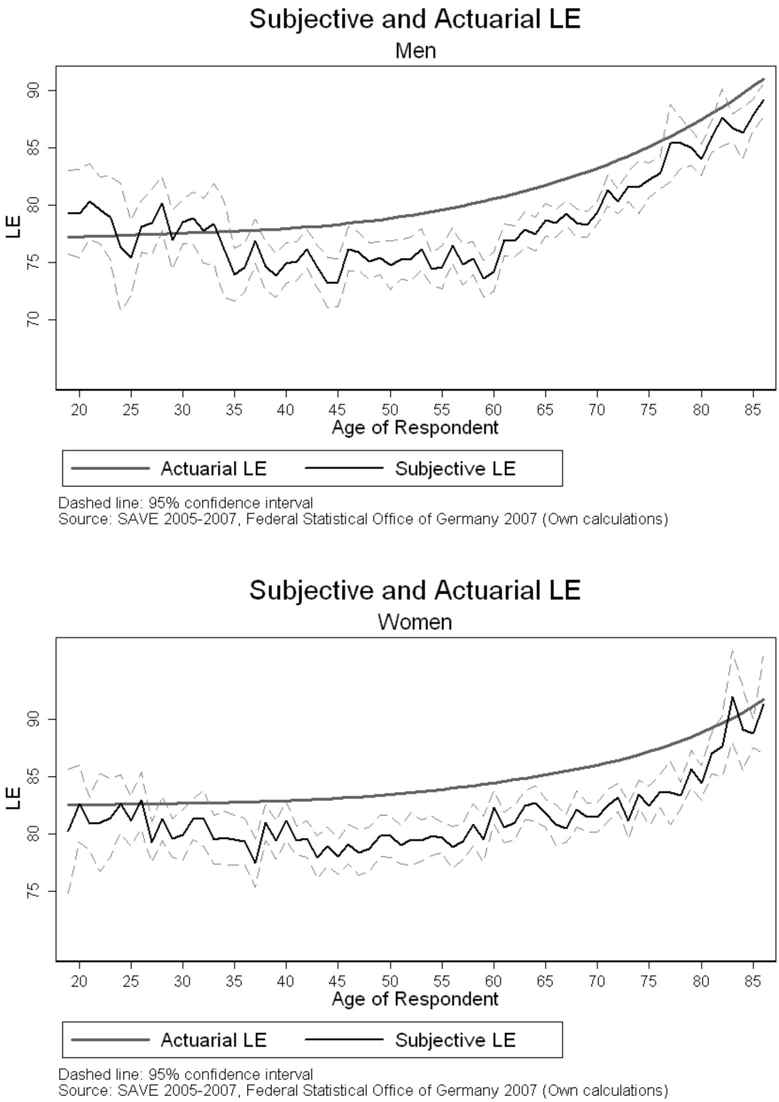

Figure 4.6: Subjective and Actuarial LE

with US data from Mirowsky (1999)[6]. Naturally the comparison can only give a brief idea due to numerous differences in the design of the two studies[7]. However, it seems evident that the strong underestimation of subjective LE is a phenomenon in the German data which differs from America.

What drives the downward bias? A *German pessimism* concerning individual LE, wide-spread *ignorance* of improvements in LE over the last 40 years, or a mixture of both? The split-up of LE questions in SAVE at least partly explains the puzzle. The fact that a large majority expects to live about as long as average (figure 4.3) makes the case for a general underestimation of average LE as explanation. We saw that at an old age, people tend to be more optimistic concerning their individual LE compared to average (figure 4.4). This could explain the convergence of mean subjective LE to actuarial LE in old age groups.

To examine this hypothesis, figure 4.8 plots the mean estimated average LE together with actuarial LE for men and women. The estimated curve lies significantly below the actuarial curve for all age groups from about 35 years on, underlining that the downward-bias of subjective LE is caused by an estimation of average LE which is too low.

Summary

Unlike Americans, Germans on average underestimate their subjective LE; this is true for men and women. The downward bias is caused by a general underestimation of average LE, which is canceled out by individual optimism only among the very old.

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[6]No differentiation between men and women is possible here given the data provided by Mirowsky (1999).

[7]The ASOC data is 10 years older, the question was asked in a different way, and the survey has been conducted via phone. For more details see section 2.2.2.

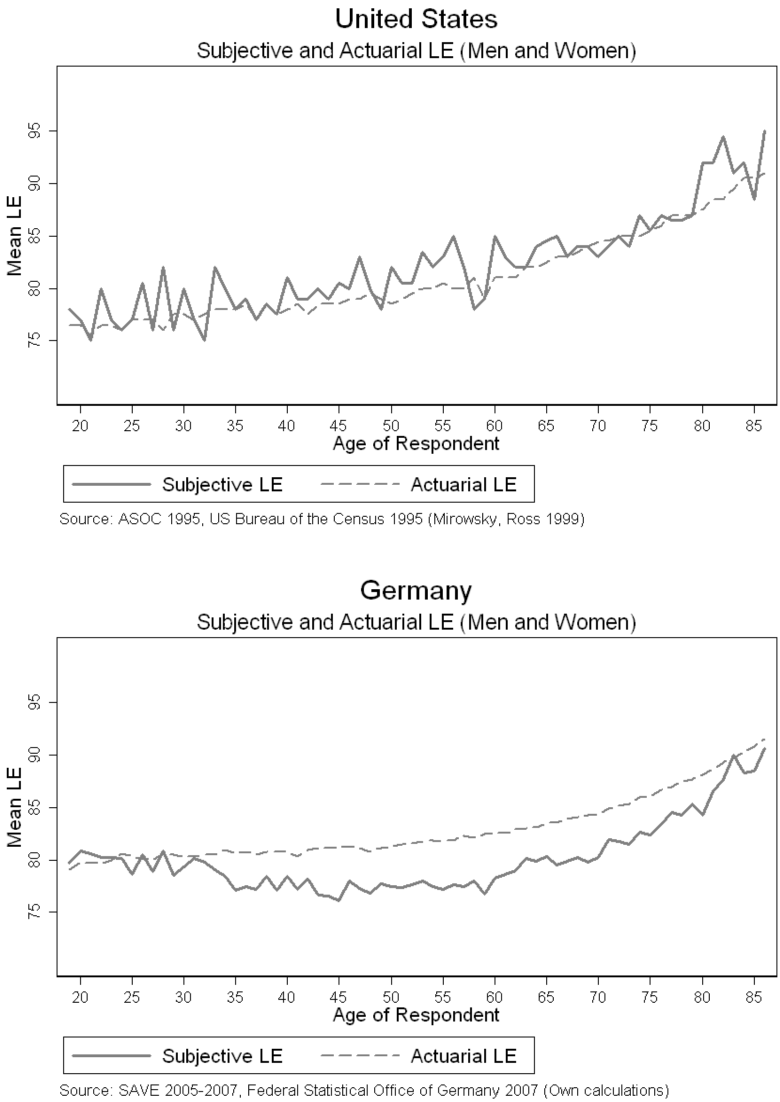

Figure 4.7: International Comparison of Subjective LE

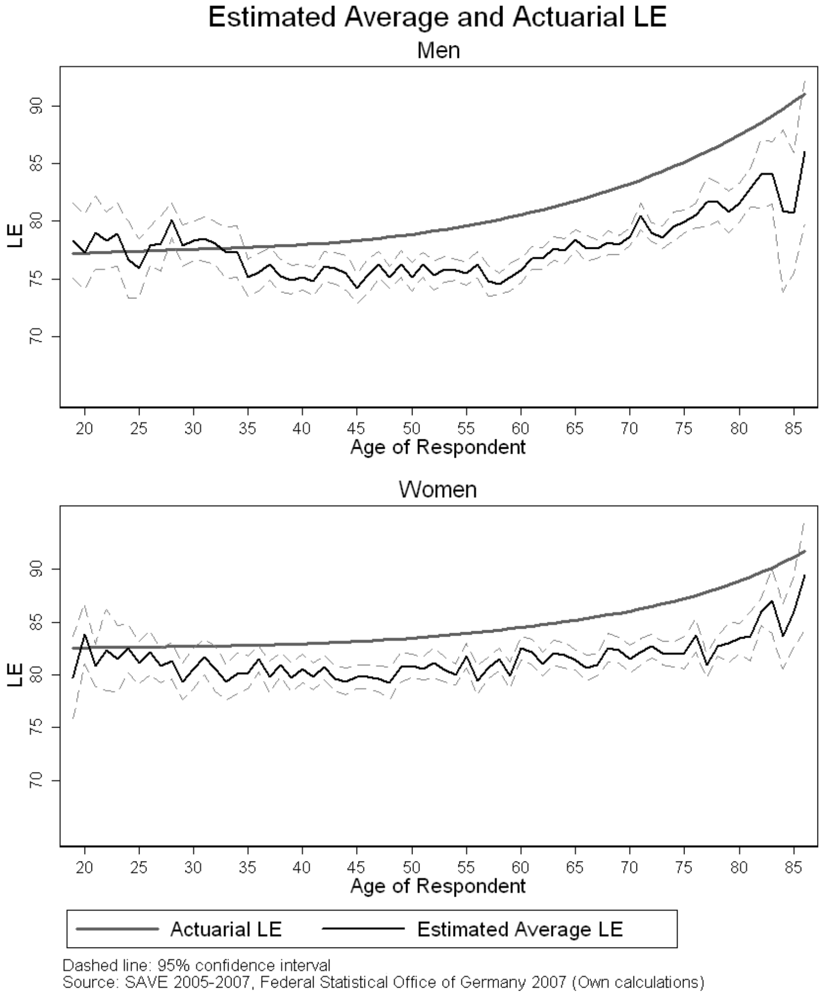

Figure 4.8: Estimated Average and Actuarial LE

4.3 Regression Analysis

The descriptive statistics presented above reveal some basic patterns of subjective LE in Germany. To make statements about the importance of different influence factors, however, a formal regression analysis is needed. This section describes the estimation strategy, followed by the regression results and an interpretation of the outcomes.

4.3.1 Regression Models

With past research and the descriptive analysis in mind, subjective LE is assumed to be a function of determinants which can be represented by seven major groups:

$$SLE = f(Sex, Age, Fam, Edu, Econ, LStyle, Health) \tag{4.3}$$

where Fam are variables describing the family situation, Edu describe education, $Econ$ are variables describing the economic situation, $LStyle$ describe lifestyle and behavior and $Health$ are health variables. In order to split up the effect of subjective LE as described in section 3.4, several empirical models are estimated.

Linear Regressions

The compound measure subjective LE (SLE) and the estimated average LE ($EstAvr$) are estimated with a linear regression model (some non-linearities are captured by the specification of variables, see section **??**). For notational ease, all independent variables are noted as x_k:

$$SLE_i = \beta_0 + \sum \beta_k x_{ik} + \epsilon_i \tag{4.4}$$

$$\mathbb{E}\left[SLE_i|\boldsymbol{x}_i\right] = \boldsymbol{x}_i'\boldsymbol{\beta} \tag{4.5}$$

As SLE can only have positive values, a left-censored tobit model would be the most precise formulation. Results however do not differ from OLS regressions[8], so only OLS estimations are presented here to get coefficients which are easy to interpret.

To determine the significance of estimators for β_k, the structure of the data has to be taken into consideration: As three waves of the survey are pooled, some observations come from the same person in different years. This is desired for the updating analysis in the next chapter, but for pooled regression it biases the standard errors of β_k-estimators because the ϵ_i from one person at different times are correlated. To account for this, the standard errors reported with regression coefficients are robust Huber-White-Sandwich estimates[9]. Finally, dummy variables are included to measure year effects.

Probit Estimations

Concerning relative expectations, two probit estimations analyze the influence of the X_k on the probability to belong to the *ExpLonger* and *ExpNotShorter*:

$$\mathbb{E}\left[ExpLonger|\boldsymbol{x}_i\right] = \Phi\left(\boldsymbol{x}_i'\boldsymbol{\beta}\right) \qquad \text{with} \quad \Phi\left(\cdot\right) = \quad Normal \text{ c.d.f.} \tag{4.6}$$

The dummy variable *ExpLonger* is 1 if a person expects to live longer than average and 0 otherwise. *ExpNotShorter* is 1 if a person believes to live longer than average or about the same as the average and 0 only if she believes to live shorter. This specification has been

[8]This is not surprising as all observations are way above zero (the smallest values are 40 for SLE and 50 for $EstAvr$).

[9] The robust variance estimator is

$$\hat{\mathbf{V}}_{\mathbf{robust}} = \hat{\mathbf{V}}\left(\sum_{k=1}^{M}\mathbf{u}_k^{(G)\prime}\mathbf{u}_k^{(G)}\right)\hat{\mathbf{V}}$$

where $\hat{\mathbf{V}} = (-\partial^2 \ln L/\partial\beta^2)^{-1}$ is the conventional variance estimator, M is the number of different persons (consisting of several observations j) and $\mathbf{u}_k^{(G)} = \sum_{j\in G_k}\partial\ln L_j/\partial\beta$ is the contribution of the kth person to $\partial\ln L/\partial\beta$.

chosen to make the interpretation of the sign comparable: Positive coefficients always refer to a longer expected life, negative coefficients to a shorter life.

Two reasons speak in favor of *two separate probit* estimations instead of *one ordered probit*: First, the ordered probit mixes two different effects, because it does not necessarily mean the same for a person to "deviate to above" from average or to "deviate to below". For example it could be that the first one is rather a psychological phenomenon (driven by optimism), while the second one is rather an information issue. Of course this is only an (untestable) hypothesis, but the two-probit-design is surely more flexible to allow for different influence structures for the effects[10].

The second reason is a rather pragmatic one: In the two-probit-design we have two distinct estimations, as the groups of people differ. Comparing results across groups then provides us with a "double check".

In order to interpret the size of effects, the tables below report marginal effects instead of probit coefficients[11]. Ruud (2000), p.755 discusses alternative approaches to measure marginal effects, concluding that sample means of the derivatives of the regression function (and sample mean differences for dummy variables, respectively) are most appropriate. Given the size of the dataset, however, it is infeasible to numerically calculate the marginal effects for each of the 7902 observations[12]. Following the convention, the partial derivatives are consequently evaluated at the sample means of the explanatory

[10] Alternatively, a multinominal logit model would allow for the same flexibility.

[11] Naturally no "marginal effects" are calculated for the constant, even though a constant is part of the estimated specification (see equation (4.6)).

[12] With the standard laptop computer used for the estimations (1.5 GHz, 540 MB RAM) it takes about 160 hours.

variables, calculating marginal effects as

$$\Phi\left(\boldsymbol{x}_i^{1\prime}\hat{\boldsymbol{\beta}}\right) - \Phi\left(\boldsymbol{x}_i^{0\prime}\hat{\boldsymbol{\beta}}\right) \tag{4.7}$$

for dummy variables, where $\boldsymbol{x}_i^a$ is $\boldsymbol{x}_i$ with the dummy variable for which the marginal effect is calculated set equal to $a = 0, 1$ and all other variables are set to their sample mean. For continuous variables (age, income) marginal effects are calculated as

$$\hat{\boldsymbol{\beta}}\,\phi\left(\bar{\boldsymbol{x}}'\hat{\boldsymbol{\beta}}\right) \qquad \text{with} \quad \phi\left(\cdot\right) = \quad \textit{Normal}\ \text{c.d.f.} \tag{4.8}$$

Weighting

Estimations are weighted as described in section 4.1.1. For a sensitivity analysis, all estimations have been repeated *unweighted*. The results (which do not differ much) are reported in the appendix, differences are also mentioned in the text.

4.3.2 Regression Results

The regression analysis provides ample evidence on the determinants of subjective LE. All results can be found in tables 4.4 and 4.6 for men and women respectively, and are discussed following the structure introduced in section 2.5.

Influence of General Characteristics

Concerning the *Age* of the respondents, subjective LE of both men and women exhibit a pattern consistent with actuarial data. Highly significant positive coefficients[13] indicate that subjective LE increases with age, and it increases at an increasing rate. The linear effect of age on estimated average LE is insignificant[14], the quadratic effect is

[13]Remember that age is normalized around the weighted mean.

[14]The unweighted regressions show a significant positive effect, which is however low in magnitude.

significantly positive. All coefficients in the probit estimations concerning estimated relative LE are positive and highly significant.

Summarizing, age has an effect on subjective LE consistent with actuarial data, while the increase in age is mostly driven by an improving relative estimation ("optimism") with age, and not so much by increased estimated average LE. Hence the descriptive results remain valid given extensive control variables.

Subjective LE does not differ significantly between *Western- and Eastern Germany*. However, the dummy variable *East* has a significant effect on estimated average LE, which is 0.7 (0.6) years lower for men (women). Apparently respondents refer to different groups as "the average", and consider the fact that actuarial LE is indeed lower in Eastern Germany (Statistisches Bundesamt (2007)).

Men: Determinants of Subjective LE

Variable	I: Subjective LE	II: Effect on Pr(longer)	II: Effect on Pr(not shorter)	IV: Estimated Average LE
General				
Age	**.0646***** (.0205)	**.00269***** (.00087)	**.00208**** (.00085)	.0187 (.0153)
Age squared	**.00711***** (.000851)	**.000139***** (.00004)	**.000192***** (.00004)	**.00447***** (.000678)
East	-.420 (0.332)	.000417 (.0199)	.0192 (.0175)	**-.701**** (.331)
Family situation				
Married	-.115 (.488)	-.0139 (.0227)	**.0395**** (.0189)	-.253 (.323)
Widowed	.795 (.968)	.0711 (.0553)	.0373 (.0395)	-.258 (.661)
Children	-.630 (.542)	-.000434 (.0250)	-.0251 (.0196)	**-.902**** (.376)
Practical help	**.767**** (.350)	-.00906 (.0165)	**.0262*** (.0145)	**.658***** (.251)
Education				
Highschool (Abitur)	**1.068**** (.553)	**.0637***** (.0234)	**-.0731***** (.026)	**.862**** (.407)
College (Hochschule)	.387 (.599)	-.0197 (.0241)	.0319 (.0217)	**.763*** (.452)
Economic situation				
Income	.171 (.161)	-.00795 (.00789)	-.00189 (.00915)	**.217*** (.125)
Income squared	-.00326 (.00585)	.000305 (.00028)	.000431 (.00051)	**-.00723*** (.00412)

Table 4.4: Determinants of Subjective LE: Regression Results (Men)

Retired	-.0440	-.0136	-.0284	.341
	(.674)	(.0230)	(.0286)	(.412)
Current unemployment	**-1.33***	-.0368	.000303	-.599
	(.697)	(.0286)	(.0281)	(.516)
Unemployment history	.0122	.0160	-.0221	-.0380
	(.464)	(.0210)	(.0185)	(.332)
Lifestyle and Behavior				
Current smoker	**-2.07*****	**-.0632*****	**-.0548****	**-1.13*****
	(.499)	(.0195)	(.0224)	(.366)
Ex-smoker	**-1.15*****	**-.0500*****	-.0267	**-.524***
	(.406)	(.0178)	(.0203)	(.305)
Weekly drinking	.436	**-.0281***	**.0373****	.304
	(.370)	(.0165)	(.0161)	(.279)
Weekly exercise	.464	**.0389****	.0247	.00285
	(.365)	(.0161)	(.0161)	(.275)
Voluntary work	**-.769****	.00362	.000806	**-.626****
	(.361)	(.0160)	(.0149)	(.265)
Health status				
Bad health	**-4.53*****	**-.0922*****	**-.258*****	-.926
	(.775)	(.0212)	(.0391)	(.582)
Long-term health prob.	**-2.72*****	**-.0979*****	**-.139*****	-.356
	(.417)	(.0180)	(.0189)	(.289)
Controls				
Year effect 2005	-.116	.0677***	.0234*	-.961***
	(.283)	(.0160)	(.0135)	(.220)
Year effect 2006	-.354	.0250	.0302**	-.953***
	(.319)	(.0153)	(.0136)	(.247)
Constant	77.7***	–	–	77.2***
	(.816)			(.639)

Figures in parenthesis are robust standard errors. ***,** and * represent statistical significance at 1%, 5% and 10% level, respectively.

Table 4.5: Determinants of Subjective LE: Regression Results (Men) -continued-

Women: Determinants of SLE

Variable	I: Subjective LE	II: Effect on Pr(longer)	II: Effect on Pr(not shorter)	IV: Estimated Average LE
General				
Age	**.0526*** **	**.00228*** **	.000521	.0128
	(.0179)	(.00061)	(.00074)	(.0139)
Age squared	**.00518*** **	**.0000788*** **	**.000139*** **	**.00267*** **
	(.000710)	(.00003)	(.00003)	(.000634)
East	-.324	-.000856	.01032	**-.537***
	(.394)	(.0153)	(.0150)	(.308)
Family situation				
Married	-.195	**-.0492*** **	.00970	-.0923
	(.419)	(.0162)	(.0164)	(.327)
Widowed	-.214	.00189	-.00294	-.275
	(.614)	(.0206)	(.0264)	(.472)
Children	-.320	-.0034	.0137	**-.746***
	(.489)	(.0182)	(.0197)	(.388)
Practical help	-.420	-.000662	**-.0243***	-.0273
	(.328)	(.0120)	(.0132)	(.272)
Education				
Highschool (Abitur)	.501	.0265	-.0380	**.737** **
	(.492)	(.0172)	(.0238)	(.372)
College (Hochschule)	.789	.0193	-.0105	**.832** **
	(.565)	(.0216)	(.0260)	(.412)
Economic situation				
Income	**.454*** **	**.0200***	**.0170** **	**.206***
	(.146)	(.0112)	(.00732)	(.120)
Income squared	**-.0155*** **	**-.00152***	**-.000837** **	-.00292
	(.00470)	(.00089)	(.00035)	(.00388)

Table 4.6: Determinants of Subjective LE: Regression Results (Women)

Retired	-.761	**-.0371****	**-.0430***	.321
	(.557)	(.0183)	(.0241)	(.369)
Current unemployment	.642	.00511	.0130	.269
	(.572)	(.0211)	(.0206)	(.467)
Unemployment history	**-.867****	-.00213	-.0243	-.357
	(.397)	(.0147)	(.0156)	(.316)
Lifestyle and Behavior				
Current smoker	**-1.79*****	**-.0252***	**-.0441****	**-1.40*****
	(.445)	(.0155)	(.0187)	(.352)
Ex-smoker	-.603	-.0160	**-.0328***	.0886
	(.411)	(.0147)	(.0199)	(.324)
Weekly drinking	**.980*****	.00986	.0148	**.663****
	(.337)	(.0137)	(.0146)	(.264)
Weekly exercise	.268	.0177	-.0130	.0214
	(.332)	(.0124)	(.0134)	(.262)
Voluntary work	.256	-.0181	.0156	.315
	(.331)	(.0127)	(.0140)	(.264)
Health status				
Bad health	**-4.53*****	**-.0882*****	**-.203*****	-.495
	(.747)	(.0117)	(.0359)	(.510)
Long-term health prob.	**-2.46*****	**-.0627*****	**-.134*****	**-.555****
	(.347)	(.0126)	(.0158)	(.278)
Controls				
Year effect 2005	.122	.0560***	-.0168	-.244
	(.267)	(.0134)	(.0141)	(.225)
Year effect 2006	-.703***	.000984	.00831	-.757***
	(.259)	(.0120)	(.0122)	(.218)
Constant	81.2***	–	–	81.2***
	(.713)			(.569)

Figures in parenthesis are robust standard errors. ***,** and * represent statistical significance at 1%, 5% and 10% level, respectively.

Table 4.7: Determinants of Subjective LE: Regression Results (Women) -continued-

Influence of Family Situation

Being *married* has no significant effect on subjective or reported average LE. The influence on relative expectations is inconclusive: Being married reduces the probability to live longer than average (significant for women), but also increases the probability to expect to live not shorter (significant for men). Together, the estimations indicate that being married makes people feeling more average. Alternatively, it could be the case that individuals with an average health and LE marry more often.

No effect of being *widowed* could be found in any regression. This does not stem from too little observations (551 individuals in the dataset are widowed). A spouse's death seems to have very little influence on subjective LE.

Similarly, no significant effect of *children* on subjective LE could be found in the data. They do however influence estimated average LE: Men with children estimate the average LE 0.9 years shorter compared to their childless counterparts, women estimate 0.7 years shorter. There is no self-evident explanation of this effect, which is also to weak to influence subjective LE.

The last characteristic of individuals' family situation under study is the question whether they receive *practical assistance* from members of the family outside the household or friends (examples given to the respondents include minor repairs, shopping, filling out forms, and help for elderly people). Among male respondents, practical help significantly increases subjective LE by 0.8 years, which is almost completely explained by a higher estimated average LE. Apparently men who receive practical help in their daily life are either better informed about improvements in LE, or they are in general more optimistic about people's longevity as they see that somebody cares about people in need. For women, however, no significant effect could be found.

Influence of Education

People having passed the German university entrance qualification *Abitur* estimate average LE 0.9/0.7 years (men/women) higher than people without Abitur, which leads to a significantly higher subjective LE for men. People graduated from *college or university* estimate average LE an additional 0.8 years higher. A possible explanation is that higher educated people refer to a reference group of other educated people, who indeed have a higher average LE. It is also very likely that better educated people are in general better informed about actuarial LE.

The influence of education measures on relative expectations is insignificant for women and inconclusive for men (positive for $ExpLonger$, negative for $ExpNotShorter$, which can again be interpreted as a trend to the average for educated individuals).

Influence of Economic Situation

For women, subjective LE increases significantly with a higher *income*, with a decreasing rate in income. About one half is caused by a higher estimated average LE, and half by improved relative estimations. For men only a higher average LE is estimated, but no significant change of relative expectations can be seen in the data.

Being *retired* leaves the estimated average LE unchanged, which makes sense as the reference group of a person, as well as the information she has, should not change in the moment of retirement. The two measures of relative expectations however worsen significantly for women (but not for men). This could be interpreted as increased melancholy once women are retired. Equally, it could just reflect nonlinearities in the influence of age (even though women are retired at very different ages).

In line with the literature, *unemployment* has a negative effect on subjective LE. For men, current unemployment reduces subjective LE by 1.3 years. For women, more important than the current situation seems to be whether one has ever been long-term unemployed (that means more than six month in a row): It reduces subjective LE by 0.9 years.

Influence of Lifestyle and Behavior

All the measures of lifestyle and behavior included in the regression significantly influence at least some of the LE variables. Most prominently, *smoking* reduces subjective LE by 2.1 years for men and 1.8 years for women. Having once been a regular smoker still has an effect about half in magnitude. A strong reduction in LE is justified given the evidence on actuarial LE of smokers (section 1.1.2), which indicates an even higher reduction. While they reflect the case of being a smoker in their subjective LE, smokers attribute this not so much to their relative position (and hence their behavior): The high reduction is mostly driven by a lower estimated average LE, which accounts for 52%/74% of the subjective LE reduction of men/women. Apparently smokers know that they live shorter than nonsmokers (the probit estimates are all negative, most of them significant); but they underestimate the magnitude of life-shortening caused by their behavior. The reported subjective LE is driven down mostly by the lower estimated average, probably because smokers have a reference group of mostly other smokers or because they are in general more ignorant concerning LE. It might also be the case that smokers overstate the percentage of smokers in the population, and consequently estimate a lower average LE.

The influence of *drinking alcohol* is inconclusive: For men both measures of relative expectation point in different directions, and for women both estimated average LE and subjective LE are significantly increased. Apparently "weekly drinker" are a group that differs in some aspects not covered by the other variables.

Doing weekly *exercise* (sports or vigorous physical activity on the job) makes men expecting a life longer than average, while the estimated average LE is not affected. It seems that people doing sports know well that physical activities improve their health and LE compared to their peers who do not. This is in line with the result that a healthy way of life is seen as major reason for a life longer than average (by those who do expect to live longer) (section 4.2.1).

Finally, *voluntary engagement* in the community is analyzed as possible determinant of subjective LE. For women, no significant effect can be found; for men the estimated average LE (and in consequence the subjective LE) decrease by 0.6 years. Different stories could explain this relationship: Maybe many of the volunteers engage in care for sick people, which makes them more aware of life-shortening diseases; maybe the group of volunteers simply represents a certain type of person (like less educated people, or rural people typically engaged in fire brigades). As no further information about the type of voluntary engagement is available, this cannot be determined. One result however remains: Voluntary engagement has no influence on relative LE compared to the average.

Influence of Health Status

By far the most important determinant of subjective LE is individual health status. People with a *bad health status* have a subjective LE which is 4.5 years lower (same for men and women). Remember that about 9% report a bad health status, compared to 48% reporting *long-term health problems*. The latter also reduces subjective LE by 2.7/2.5 years (men/women). Out of the people in a bad health status, 99% also report long-term health problems, so in sum the 10%

with the worst health status have a subjective LE which is about 7 years shorter, and the 39% who do not report a bad health status but still have long-term health problems still have a subjective LE 2.5 years shorter. These determinants are by far the most important in magnitude.

Unlike many determinants before, the health status does not affect the estimated average LE at all, but drives tremendously down relative LE. In contrast to smokers for instance, people with a bad health status seem to realize very well that their condition is specific to them and therefore expect to live shorter than average (while the estimated average is unaffected).

4.3.3 Discussion

While the construction of the dataset as well as variable construction and regression design try to avoid possible biases in the estimations as much as possible, no analysis using real-world panel data is perfect. Consequently, the analysis presented above has limitations and raises some doubts. The most important possible objections are discussed in the following paragraphs.

Non-Representativeness of Survey Participants

As noted above, observations are weighted along the dimensions age and income in order to reach representativeness for Germany. However, long-term studies using the German SOEP data showed that the average (actuarial) LE of survey participants is slightly higher than life tables would predict (Schnell and Trappmann (2006)). The reason is that persons in a very bad state of health excessively refuse to participate or continue the survey (Lampert, Kroll, and Dunkelberg (2007)). Most likely the same is true for the SAVE dataset.

This type of sample selection bias however does not affect the robustness of our main results. Descriptive statistics showed a downward bias of subjective LE - a sample selection would lead to an underestimation of the effect. The same is true for the regression results concerning the influence of health variables on subjective LE. If the group of bad-health-individuals in the sample would consist only of relatively healthy people (because the very unhealthy individuals dropped out of the panel), the importance of health status as determinant of subjective LE would be underestimated. Insofar, both effects are robust. For the other regression coefficients (education, income etc.) the effect is not so clear. However, no plausible reason explains why a sample selection of the very unhealthy should affect the distribution of education in the sample. And the income distribution is adjusted via weighting.

Systematically Implausible LE Estimations

As described is section 4.1.1, some participants state an obviously implausible subjective LE which is lower than their current age. The deletion of these observations could bias the analysis, as the indication of an implausible LE might not occur randomly. However, implausible answers appear very seldom, and the 62 implausible answers distribute quite even: For men only 3 age classes have more than 2 implausible answers, for women no age class.

To see if implausible answers about subjective LE occur randomly, a simple selection model is estimated, in line with all analysis in this paper separately for men and women:

$$\mathbb{E}\left[Implausible|\boldsymbol{x}_i\right] = \Phi\left(\boldsymbol{x}_i'\boldsymbol{\beta}\right) \qquad \text{with} \quad \Phi\left(\cdot\right) = \quad Normal \text{ c.d.f.} \tag{4.9}$$

The dummy variable *Implausible* is 1 if a person states an implausible subjective LE and 0 otherwise. The probit coefficients of an unweighted regression are summarized in table 4.8 (standard errors are clustered as described in section 4.1.1). An interpretation of the coefficients might be misleading due to the small number of implausible observations (41 men/21 women, in a regression with 23 independent variables). However, a couple of coefficients are significantly different from zero, so it cannot be ruled out that the exclusion of implausible responses biases the analysis.

Influence on Probability to Report Implausible Subjective LE

	Men		Women	
Age	.079581***	(.0236501)	.0294013***	(.00916)
Age squared	.0004918	(.0005775)	.0007749**	(.0003859)
East	.2980743	(.1950328)	-.4217431**	(.2098739)
Married	-.1619043	(.1693728)	-.1200174	(.2719678)
Widowed	-.257785	(.2745856)	-.2544146	(.3053988)
Children	-.3767487**	(.1949592)	.2645622	(.2482102)
Practical Help	-.1883816	(.1692296)	.1704562	(.1768927)
High school (Abitur)	-.4175799	(.2865708)	-[a]	
College (Hochschule)	.0916776	(.2838075)	-[a]	
Income	.0269993	(.1079878)	-.2376209*	(.1389443)
Income squared	-.0016419	(.0050466)	.0167796**	(.0074072)
Retired	-.3313734	(.2938231)	-.0188226	(.2718441)
Current unemployment	1.001609***	(.3793931)	.4859143	(.390884)
Unemployment History	-.4901231**	(.2175534)	.1507961	(.2213986)
Current smoker	.4071759*	(.2158613)	.0748209	(.2281655)
Ex-smoker	-.1288544	(.1731651)	-.070165	(.270934)
Weekly drinking	-.1957761	(.1525808)	-.7119718**	(.2869914)
Weekly exercise	.1090337	(.1460902)	.4038988**	(.189944)
Voluntary work	.2001357	(.1499111)	-.394544*	(.2148008)
Bad health	.4675475**	(.1993365)	.7890664***	(.1829867)
Long term health prob.	-.0638602	(.1719378)	-.116144	(.2273461)
Year effect 2005	-.0223418	(.1870715)	-.2519767	(.2254913)
Year effect 2006	.039822	(.1754758)	-.3852816*	(.2282698)
Constant	-3.597045***	(.4832002)	-3.002437***	(.435779)

[a]Education variables perfectly predicted failure for women and have therefore been excluded

Figures in parenthesis are robust standard errors. ***,** and * represent statistical significance at 1%, 5% and 10% level, respectively.

Table 4.8: Selection Model "Implausible Answers"

To be sure, regression analyses have been repeated with a dataset including the implausible answers as sensitivity analyses (results are reported in tables A.5 and A.7 in the appendix). The coefficients for income effects among male individuals are insignificant in the regression for estimated average LE. While they are the same in magnitude this is caused by increased noise from the implausible observations. For women, the coefficient for education (high school) almost doubles - which stems from the fact that none of the implausible respondents (reporting a very low subjective LE) has passed the Abitur.

All other coefficients remain significant and in the same magnitude in all regressions and probit estimations. Hence the treatment of implausible answers does not affect the results presented in this chapter.

Misunderstanding of Survey Questions

Finally, one could argue that people systematically misunderstand the survey questions concerning LE. If they understand "What average age do you believe men/women of your *cohort* will reach?" instead of the correct question "What average age do you believe men/women of your *age* will reach?", they would report something different than we expect to measure. The same is true for the question "If you think of your own situation and your state of health, do you think that, in comparison to other men/women of your *age group*, your lifespan will be... shorter/about the same/longer?" which could be misunderstood in a similar way.

In principal, we can never be totally sure what people actually think when they read a survey question, probably only a in-depth interview right after posing the question could reveal the way of thought. However, in the special case of this question it seems very unlikely that people by large misunderstand the question. The formulation is very straightforward, and no reason is visible why people should not understand the simple words "of your age".

In addition, some evidence in the data points toward the case that at least most people do not confuse "age" and "cohort" in the question:

As will be shown in the next chapter, a time series of the same person being asked several years in a row shows an estimated average LE which increases with every year a person gets older. This makes sense for the right version of the question, as LE increases with age. It contradicts however the "cohort" version of the question, as a cohort LE does not increase while an additional years passes[15]. So while it cannot be ruled out that some individuals (esp. in very old years) misunderstand the question in the described way, this is surely not the case for the largest part of the sample. Besides it should be kept in mind that all results concerning the compound measure "subjective LE" remain valid however the questions are understood, as in the case of a misunderstanding, the personal additional LE compared to average will be correspondingly higher.

[15]Besides the technological progress in health care etc. which is negligible for the time span of one year.

Chapter 5

Updating of Subjective Life Expectancy: Testing a Simple Model

Chapter 4 evaluated the most important determinants. In order to fully understand subjective LE, economists additionally analyze people's updating when new information concerning their LE become available. Past research analyzed updating of survival probabilities if health shocks occur. Using the SAVE data introduced in the last chapter, this chapter goes beyond available evidence in two aspects: First, instead of the development of subjective survival probabilities, the updating of the more intuitive measure LE (a number of years instead of a probability) is analyzed. Second, subjective LE is split up in line with the analysis above, leading to a deeper understanding how people update their LE if they experience a health shock.

5.1 Model

How people change their expectations when new information is available is a question of high relevance in the study of subjective LE. This section develops a simple updating model of subjective LE if idiosyncratic shocks occur, which will be tested using SAVE data.

5.1.1 Background and Motivation

The literature shows that some efforts have been made to understand updating procedures (section 2.4.4). The theoretical framework is the theory of choice under uncertainty. While the discussion in psychology centers on the question whether probability is at all an appropriate formalism to model mental processes in the case of uncertainty (Henrion (1999)), economic theory has developed the expected utility framework to analyze choices under uncertainty. The case of an unavailable objective probability distribution and the need of subjective expectations has been formalized by Savage (1954) within the rational utility maximization framework as *subjective probability theory* and is part of mainstream economic theory (see Mas-Colell, Whinston, and Green (1995), p. 205-208).

A particular updating rule, which is often assumed to be applied by rational individuals, is the *Rule of Bayes*. Together with certain assumptions concerning the distribution of the prior, it requires to take an average of the old expectation and the new information, weighted by the information content and precision of the information. This is implemented in the papers who study the updating of subjective survival probabilities (see section 2.4.4). The application of this framework requires however the formulation of the expectations as probabilities. As discussed above, thinking in probabilities is not necessarily something people are used to, and in our special case of LE, subjective LE (measured in years) is an alternative measure of what people think how much lifetime remains. The last chapter analyzed determinants of this measure for Germany, and this chapter explores how people update their subjective LE.

5.1.2 Updating Model

Given the fact that LE is measured in years, the Baysian updating framework cannot be directly applied. One possibility would be to proceed in an analogical way and assume the new subjective LE to be a weighted average of the old subjective LE and some new information. The weighted average makes sense for probabilities, however it is not apparent why individuals should apply such a rather complex procedure when they have to adjust an absolute number of years. This study suggests that individuals proceed using a simple heuristic, which requires them to add or subtract some years from their original LE if any new information requires them to adjust it. That is

$$SLE_t = SLE_{t-1} + \Delta \tag{5.1}$$

where Δ is the (positive or negative) adjustment of LE. In our panel, individuals are interviewed every year, hence t are years. Adjustment of subjective LE between the years can be made for at least two reasons: First, actuarial LE increases with age, hence an individual should increase subjective LE every year just for being older than the year before ($\Delta_{Age\ Adjustment}$). This captures the non-occurrence of negative health shocks as well as positive health shocks and growing optimism with age. LE increases with an increasing rate in age, hence the annual adjustment should also increase in age. Summarizing, the supposed age adjustment is

$$\Delta_{Age\ Adjustment} = \alpha_0 + \alpha_1 Age \qquad \text{with} \quad \alpha_0, \alpha_1 > 0 \tag{5.2}$$

The second reason for adjustments are idiosyncratic shocks ($\Delta_{idiosyncratic}$). The analysis in chapter 4 singled out the individual health situation as most important determinant of subjective LE, so the following analysis studies health shocks. While positive health shocks are imaginable[1], we focus on the prevalent event of *negative health shocks* (like the unexpected diagnosis of a severe illness or the unexpected worsening of medical conditions). If negative health shocks are measured with a dummy variable D_{shock} which is 1 if a shock occurred and 0 otherwise, the supposed idiosyncratic adjustment is

$$\Delta_{idiosyncratic} = \beta\, D_{shock} \qquad \text{with} \quad \beta < 0 \tag{5.3}$$

Putting the pieces together, we get our model for the updating of subjective LE,

$$SLE_t = SLE_{t-1} + \underbrace{\alpha_0 + \alpha_1 Age}_{\Delta_{Age\ Adjustment}} + \underbrace{\beta\, D_{shock}}_{\Delta_{idiosyncratic}} \tag{5.4}$$

which can be rearranged as

$$SLE_t - SLE_{t-1} = \alpha_0 + \alpha_1 Age + \beta\, D_{shock} \qquad \text{with} \quad \alpha_0, \alpha_1 > 0;\ \beta < 0 \tag{5.5}$$

Looking at the adjustment of estimated average LE ($LE_{avr,t} - LE_{avr,t-1}$), equation (5.5) should apply with the same conditions for α_0, α_1. β instead should be equal to zero, as an idiosyncratic shock contains no information on the average LE of an age group. Finally, the relative estimations of individual LE compared to average should also be updated if a health shock occurs. If people learn in a rational way, we should see

$$Pr\,(C = \textit{shorter})_t > Pr\,(C = \textit{shorter})_{t-1} \quad \text{if} \quad D_{shock} = 1 \tag{5.6}$$

$$Pr\,(C = \textit{longer})_t < Pr\,(C = \textit{shorter})_{t-1} \quad \text{if} \quad D_{shock} = 1 \tag{5.7}$$

---

[1] For instance, the diagnosis that a previously known tumor surprisingly stopped growing.

5.2 Data and Variables

To test the updating model of subjective LE, we exploit the panel dimension of the SAVE survey.

5.2.1 Panel Dataset

We base our analysis on the three SAVE waves 2005-2007, applying exactly the same clearing up and imputation procedure as described in section 4.1.1. For this chapter's analysis, all regressions are unweighted - the number of people experiencing health shocks is too low to make representative statements for the German population at whole. Besides, the purpose of this chapter is to test a simple model of updating behavior, and there is no need to put higher or lower weight on observations for that.

5.2.2 Variable Construction

In addition to the variables already used in chapter 4, an indicator of negative health shocks is generated. The survey does not ask explicitly for health events between the waves, so shocks are inferred from the following information: Survey participants indicate which illnesses or symptoms they suffer from. The list of possible illnesses has been extended over the years, but for all years under study the following options are offered: *Heart disease, high blood pressure, high cholesterol level, stroke or circulatory problems affecting the brain, chronic diseases of the lung or asthma, cancer or malignant tumors excluding minor cases of skin cancer, stomach ulcers or duodenal ulcer.* Table 5.1 gives an idea how widespread each of these symptoms are.

If a person did not indicate to suffer from an illness in the year before, but now indicates to suffer from it, we call it a negative health

Overview of Illnesses and Health Shocks

Illness	Frequency	Number of Shocks
Heart disease	14.6%	149
High blood pressure	37.8%	254
High cholesterol level	22.5%	251
Stroke	3.2%	36
Chronic Lung disease	10.2%	100
Cancer	5.7%	75
Stomach/duodenal ulcer	4.4%	81
Negative Health Shock	–	767
Long-term health problems	47.0%	468

Table 5.1: Overview Health Variables

shock of that particular illness. Consequently, a health shock can only be determined for two years (2006 and 2007), as we need the information from the year before to identify health shocks (which parallels the measures on LE: There we also need the information from the year before to determine the adjustment). This results in 4141 "second-year observations", which constitute the dataset used in this chapter. The last column in table 5.1 shows that high blood pressure and high cholesterol level are the most common health shocks, in contrast to stroke and cancer who are rather rare.

All shocks are combined in the measure *NegativeHealthShock*, which is 1 for a certain individual who experienced at least one shock between the waves and 0 otherwise. Naturally this measure contains some noise as respondents might forget a certain symptom once in a while. Table 5.2 shows how the respondents' indications of illnesses vary over time.[2] Besides negative shocks, also a significant number of *positive* health shocks occur (people stating an illness in period $t-1$ which is not stated in period t), while positive shocks appear

[2]The table describes the pattern for those respondents who took part in all three waves (2005, 2006, 2007). As described in section 5.2.1, for the construction of health shocks also individuals appearing in two waves are used.

less often than negative shocks. The phrasing of the health question does not rule out positive shocks, as specific illnesses might have improved and be no longer relevant for a person. In any case, the existence of positive shocks does not reduce the information content of the measure *NegativeHealthShock*; the following analysis will show that it is sufficiently precise to have a significant updating effect.

For additional tests, an alternative measure of health shocks is constructed using the variable on *long-term health problems* which has already been described in the last chapter: *ChronicHealthShock* is 1 if a respondent suffers from long-term health problems now, but did not have long-term health problems in the last period, and 0 otherwise. The correlation between the two measures is quite low (0.0916), indicating that *ChronicHealthShock* measures somewhat different health shocks than *NegativeHealthShock*, and a separate analysis of the alternative variable provides additional evidence.

Illness Indication 2005-2007

Illness	**nnn**	**yyy**	**nny**	**nyy**	**ynn**	**yyn**	**nyn**	**yny**
Heart disease	76.0%	8.5%	4.1%	2.7%	3.9%	0.7%	2.6%	1.4%
High blood pressure	45.4%	30.0%	3.9%	7.0%	5.6%	2.5%	4.1%	2.1%
High cholesterol level	63.4%	9.2%	5.2%	5.8%	6.3%	1.8%	4.7%	3.6%
Stroke	95.6%	0.8%	0.7%	0.7%	0.9%	0.3%	0.8%	0.4%
Chronic Lung disease	82.4%	4.7%	1.4%	1.4%	5.8%	1.2%	2.1%	1.0%
Cancer	91.0%	2.3%	2.3%	1.0%	0.8%	0.4%	1.9%	0.3%
Stomach/duodenal ulcer	90.3%	1.7%	2.5%	1.7%	0.9%	0.4%	2.1%	0.5%
Long-term health problems	40.9%	30.3%	6.9%	6.9%	4.0%	3.0%	4.1%	3.9%

Answers to the question whether the respondent suffers from a certain illness in the years 2005, 2006, 2007 (y=yes, n=no). Only respondents appearing in all three waves.

Table 5.2: Panel Responses Concerning Illnesses

5.3 Descriptive Analysis

Before testing the updating model formally, this section provides a couple of descriptive statistics which give a first impression of updating processes in the SAVE data.

To start with, figure 5.1 shows the distribution of adjustments in subjective LE between two waves (a kernel density estimate is used to smooth the focal points at 0, +/- 5, +/- 10 years). The curve for individuals having incurred a health shock during the last year lies left of the curve for individuals without health shocks, indicating that a health shock leads some people to reduce their LE. The difference between the graphs is small, the comparison in table 5.3, however, is more clear. The mean adjustment without health shock is $+.23$ years, while the mean adjustment in the case of health shock is $-.57$ years. The absolute value of subjective LE also has a lower mean for the health-shock group. A t-test shows that both measures are significantly different between the groups with- and without health shocks (t-statistics: 3.10 and 2.78).

Means of Subjective LE and Adjustments

	Without Health Shock	**With Health Shock**
Subjective LE	78.99	78.12
Adjustment subjective LE	.2277	-.5750
Estimated average LE	79.28	78.75
Adjustment estimated avr LE	.4364	.1447

Table 5.3: Health Shock Heterogeneity in LE

Remarkably, the mean adjustment of estimated average LE is positive for individuals with and without health shocks, and the difference between the absolute values of estimated average LE is lower than the difference between subjective life expectancies. T-tests show that

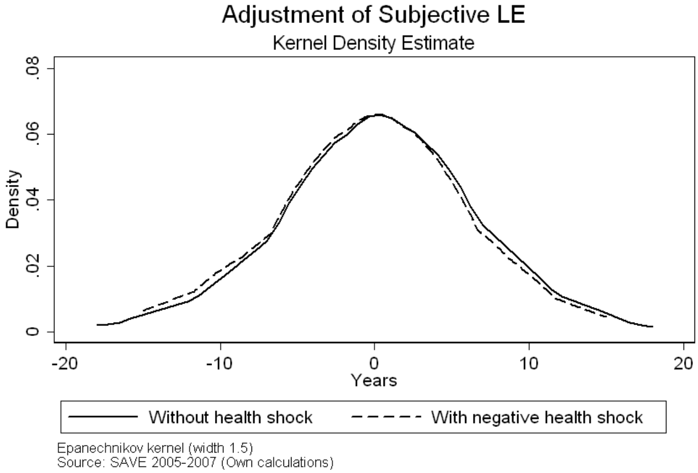

Figure 5.1: Adjustment of Subjective LE

differences in *EstAvr* and the respective adjustments are not significantly different between the groups with- and without health shock (t-statistics: 1.66 and 1.44). It seems that people (correctly) primarily update their LE relative to their same-age peers and (correctly) increase estimated average LE to reflect their older age.

This hypothesis is supported by the dummy variables measuring LE compared to average. As discussed, respondents are asked to classify themselves into three groups, depending on whether they believe to live shorter, longer or about the same as average. Table 5.4 shows transition matrices for the switching behavior between two waves of SAVE, separately for individuals with and without health shocks. Without health shocks, 15.8% switch to a "worse" group[3], compared to 20.1% if a health shock occurred. The difference is

[3]"Same" instead of "Longer"; or "Shorter" instead of "Longer" or "Same".

mainly caused by the higher number of individuals switching from "Same" to "Shorter" (10.3% compared to 7.0%). To parallel the analysis from the last chapter, the switching behavior is also shown in terms of the groups used for binary comparisons ("Expect longer" and "Expect not shorter", table 5.5).

Transition Without Health Shock

From To	**Longer**	**Same**	**Shorter**
Longer	7.6%	8.2%	0.6%
Same	6.4%	53.9%	7.0%
Shorter	0.6%	7.3%	8.5%

improvement: 14.3 % worsening: 15.8 %

Transition With Health Shock

From To	**Longer**	**Same**	**Shorter**
Longer	7.6%	9.0%	0.8%
Same	5.4%	50.5%	10.3%
Shorter	0.8%	6.7%	9.1%

improvement: 12.9 % worsening: 20.1 %

Table 5.4: Transition Matrices (LE Compared to Average)

Transition between LE Groups

	Leave Group "Expect Longer"	**Leave Group "Expect Not Shorter"**
Without Health Shock	8.8%	7.6%
With Health Shock	9.8%	11.1%

Table 5.5: Transition Probabilities (LE Compared to Average)

5.4 Regression Analysis

To see whether the descriptive evidence allows inferences, regression analyses are performed to formally test the model. This section describes the regression setup and formulates hypotheses to test the theoretical updating model (equation (5.4)).

5.4.1 Regression Models and Formal Hypothesis

Following the theoretical model developed above, empirical models are formulated alike the specifications in chapter 4:

$$\mathbb{E}\left[Adj\_SLE_i | Age_i, D_{shock_i}\right] = \alpha_0^{SLE} + \alpha_1^{SLE} Age_i + \beta^{SLE}\ D_{shock_i} \tag{5.8}$$

$$\mathbb{E}\left[Adj\_Avr_i | Age_i, D_{shock_i}\right] = \alpha_0^{Avr} + \alpha_1^{Avr} Age_i + \beta^{Avr}\ D_{shock_i} \tag{5.9}$$

$$\mathbb{E}\left[LEL_i | Age_i, D_{shock_i}\right] = \Phi\left(\alpha_0^{L} + \alpha_1^{L} Age_i + \beta^{L}\ D_{shock_i}\right) \tag{5.10}$$

$$\mathbb{E}\left[LENS_i | Age_i, D_{shock_i}\right] = \Phi\left(\alpha_0^{NS} + \alpha_1^{NS} Age_i + \beta^{NS}\ D_{shock_i}\right) \tag{5.11}$$

where the adjustments are defined as
$Adj\_SLE_i = (SLE_t - SLE_{t-1})_i$ and
$Adj\_Avr_i = (EstAvr_t - EstAvr_{t-1})_i$, respectively. LEL_i ("**L**eave **E**xpect **L**onger") is a dummy variable which is 1 if a person expected to live longer than average in the last wave and now expects to live about the same or shorter. Analogously, $LENS_i$ ("**L**eave **E**xpect **N**ot **S**horter") is a dummy variable which is 1 if a person expected to live longer than average or about the same in the last wave and now expects to live shorter. $\Phi(\cdot)$ is a *Normal* c.d.f. Reported standard errors of coefficients are robust in the sense that they allow

for intra-personal correlation (as described in section 4.3.1), and a dummy captures year effects[4]. To allow gender-specific differences, all regressions are done separately for men and women.

To test whether survey participants in SAVE update their subjective LE rationally in a way described in the model (5.4), the following conditions have to hold:

1. $\alpha_0^{SLE} > 0$
2. $\alpha_1^{SLE} > 0$
3. $\beta^{SLE} < 0$
4. $\alpha_0^{Avr} > 0$
5. $\alpha_1^{Avr} > 0$
6. $\beta^{Avr} = 0$
7. $\beta^{L} > 0 \vee \beta^{NS} > 0$

Conditions 1 and 4 secure that people take into account the growing LE with age, conditions 2 and 5 are required to reflect the fact that LE increases quadratically with age. Condition 3 secures that some people reduce their subjective LE if they experience a negative health

[4]The year dummies are included to make sure that the other variables' effects are not driven by year effects. Hence the coefficients do not affect this chapter's results. It is however remarkably that in most regressions the year dummy 2006 is significantly negative and high in magnitude. One possible explanation is that SAVE consists of different subsamples (Börsch-Supan, Coppola, Essig, Eymann, and Schunk (2008), p.36). From 2006 on, a large access panel- refresher group enters the sample. To explore whether good health and optimism of the refresher group drive the year effects, regressions are repeated including a dummy for the access panel. Results are reported in the appendix (tables A.9 and A.10). The access panel-dummy is negative, and the year effects stay almost the same. All results concerning the updating model remain the same in significance and magnitude.

shock, while condition 6 says that the estimated average LE is *not* affected by individual health effects. Finally, condition 7 requires that some people change their relative LE downwards because of health shocks. Putting the pieces together, the model described in equation (5.4) can be maintained if the alternative hypothesis of conditions 1-7 can be rejected[5].

5.4.2 Regression Results

Parameter estimates together with standard errors are presented in tables 5.6 and 5.7, for men and women respectively. First, the constant α_0 is positive for all specifications of *Adj_SLE* and *Adj_EstAvr*, significantly larger than zero for 7 out of 8 specifications. Hence the hypothesis that people do not account for growing LE with age can be rejected; on average respondents realize that their subjective LE increases with every year they live. The coefficient α_1, which measures the quadratic influence of age, is significantly positive only for women (in all specifications). For men we cannot reject the hypothesis that people are unaware of their LE increasing *at an increasing age* in our data, while women on average do increase their subjective LE and the estimated average LE when they get older[6].

Second, the parameter β is significantly negative in almost all specifications of *Adj_SLE*. The first specification, a newly appearing ill-

[5]Condition 6 requires that a coefficient is exactly zero. Naturally the alternative hypothesis (that the variable is unequal zero) cannot be rejected if the sample is unequal the full population. So all we can do is to look whether the null hypothesis can be maintained given the data.

[6]To be consistent with regression results in the last chapter, the significance levels of coefficients in tables 5.6 and 5.7 (the "stars") are significance levels for the null hypothesis $\kappa \neq 0$, where κ is any coefficient. To be exact, however, the hypothesis $\kappa \geq (\leq) 0$ has to be rejected in order to maintain the conditions stated above. There could be a situation where the stated coefficient is not significantly different from zero, but significantly smaller (larger) than zero. However, this is not the case for our results.

Influence on LE Adjustments (Men)

	Adj_SLE		Adj_EstAvr	
	I	II	I	II
Negative health shock (β)	**-.813***		-.186	
	(.450)		(.341)	
Chronic health shock (β)		**-1.62*****		-.339
		(.537)		(.448)
Age (α_1)	.000257	-.00174	.00382	.00334
	(.00860)	(.00843)	(.00727)	(.00720)
Constant (α_0)	**.533***	**.598****	**.920*****	.932
	(.362)	(.206)	(.157)	(.159)
Year dummy 2006	-.668*	-.771**	-.658**	-.681**
	(.362)	(.358)	(.289)	(.282)

Updating of LE compared to Average (Men)

	Leave "Expect Longer"		Leave "Expect not shorter"	
	I	II	I	II
Negative health shock (β)	.00639		**.263*****	
	(.0983)		(.0974)	
Chronic health shock (β)		**.183***		**.209***
		(.112)		(.117)
Age (α_1)	**.0117*****	**.0101*****	-.00276	-.000880
	(.00291)	(.00249)	(.00256)	(.00231)
Constant (α_0)	**-1.47*****	**-1.43*****	**-1.28*****	**-1.34*****
	(.0704)	(.0573)	(.0628)	(.0539)
Year dummy 2006	.200**	.146*	-.223**	-.113
	(.0862)	(.0793)	(.0892)	(.0839)

Figures in parenthesis are robust standard errors. ***,** and * represent statistical significance at 1%, 5% and 10% level, respectively.

Table 5.6: Regression Results Updating (Men)

Influence on LE Adjustments (Women)

	Adj_SLE		Adj_EstAvr	
	I	II	I	II
Negative health shock (β)	**-.742***		-.333	
	(.422)		(.360)	
Chronic health shock (β)		**-1.75*****		-.333
		(.515)		(.409)
Age (α_1)	**.0182****	**.0149***	**.0190****	**.0178****
	(.00919)	(.00895)	(.00794)	(.00781)
Constant (α_0)	**.577*****	**.681*****	**.653*****	**.646*****
	(.199)	(.202)	(.171)	(.173)
Year dummy 2006	-.833**	-.927**	-1.05***	-1.09***
	(.364)	(.366)	(.307)	(.306)

Updating of LE compared to Average (Women)

	Leave "Expect Longer"		Leave "Expect not shorter"	
	I	II	I	II
Negative health shock (β)	.0282		**.182***	
	(.108)		(.104)	
Chronic health shock (β)		**.314*****		**.439*****
		(.114)		(.113)
Age (α_1)	.00390	**.00584****	.00458	**.00539****
	(.00309)	(.00273)	(.00295)	(.00275)
Constant (α_0)	**-1.47*****	**-1.51*****	**-1.45*****	**-1.54*****
	(.0665)	(.0567)	(.0667)	(.0579)
Year dummy 2006	.0640	.0638	-.149	-.0712
	(.0915)	(.0860)	(.0945)	(.0904)

Figures in parenthesis are robust standard errors. ***,** and * represent statistical significance at 1%, 5% and 10% level, respectively.

Table 5.7: Regression Results Updating (Women)

ness (*NegativeHealthShock*) leads people to reduce their subjective LE on average by 0.81 years for men and 0.74 years for women (significantly negative). The alternative health shock measure, a newly appearing chronic health problem (*ChronicHealthShock*) has an even larger effect: 1.61 years reduction for men and 1.75 years reduction for women. Looking at the estimations concerning the transition probability between the groups with different relative LE, we find that a negative health shock strongly increases the probability to switch to the group "Expecting life shorter than average" (significant for men and women in both specifications). In contrast, the influence on the probability to leave the group "expecting life longer than average" is significantly positive only in the second specification (*ChronicHealthShock*) and smaller in magnitude. Hence we can confirm the idea from the descriptive analysis (table 5.5) that the typical dynamic is that people expecting to live about as long as average switch to the group "shorter than average" when they experience a health shock.

While a negative health shock strongly influences subjective LE, the respective parameter (β^{Avr}) is insignificant for all specifications of Adj_EstAvr, the adjustment of estimated average LE. We can maintain hypothesis 6; people (correctly) do not change their estimation of average LE if they personally suffer from an illness.

Summary

To summarize, people increase estimated average LE and their personal subjective LE as they get older, women quadratically with age. A negative health shock reduces subjective LE - because people then expect to live shorter than average.

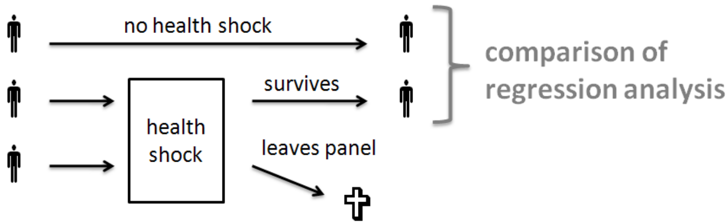

Figure 5.2: Illustration of Selection Effect

5.4.3 Discussion

Concerning limitations of the regression setup, most of the points made in section 4.3.3 remain valid. In addition, a selection effect is relevant for the panel setup: Only respondents who stay part of the panel for a second year can be used for the analysis. We analyze health shocks; naturally a health shock can be more or less severe. A very bad health shock may lead people to drop out of the sample (either because they decease or because they move to nursing homes and are no longer reachable for the interviewer). In consequence, our analysis only includes health shocks which are not too severe. Figure 5.2 illustrates the selection effect.

The findings, however, should not be challenged by this possible bias: We find respondents to significantly reduce their subjective LE due to a health shock. If this is true for the relatively light health shocks in the sample, this is even more true for the population with heavier health shocks. The selection bias rather underestimates than overestimates the effect.

Chapter 6

Conclusion

This chapter summarizes main findings of the empirical analyses, in the light of the questions posed in chapter 3. Implications are discussed, and two projects for future research are sketched out.

6.1 Summary and Implications

Given the relevance of subjective LE for individual decision-making, this study aims to understand the formation and updating of subjective LE. A synopsis of literature from different sciences summarizes what is known, but also identifies several open questions. We try to answer them with data from the German SAVE study.

As starting point, basic patterns of subjective LE in Germany are revealed. We show that Germans on average underestimate their subjective LE - the mean of subjective LE lies even below the curve of actuarial LE from life tables (which do not account for technological progress). The underestimation occurs in a wide age range for both men and women. Given the importance of personal decisions concerning old-age provision, the underestimation of subjective LE is a serious issue for Germany (in contrast to the United States, where estimates seem to be quite accurate).

To analyze the causes of LE underestimation, subjective LE is split up in estimated average LE and individual relative expectations. About two thirds of the Germans expect to live about as long as average; consequently the underestimation of subjective LE is caused by an underestimation of average LE. We conclude that we have do not have to address individual pessimism, but wide-spread ignorance concerning actuarial LE in Germany.

Besides basic patterns of subjective LE, we explore the relative importance of determinants. A joint analysis of many factors addressed in the literature shows that by far the most important determinant is the individual health situation. In a joint regression, the importance of economic variables is rather small. Smoking significantly reduces subjective LE, but this is mostly driven by a lower estimated average LE. In contrast, the better educated a person is, the higher are estimates of average LE. This supports the idea that the underestimation of average LE is caused by a lack of information.

Finally, a simple updating model is successfully tested in the panel data. Estimations show that individuals update their subjective LE quite rationally: A negative health shock leads people to adjust their individual LE compared to average, while estimated average LE remains unchanged. The updating dynamics show that people do adjust their subjective LE on a regular basis, and raise the hope that a more precise general knowledge of average LE can lead to a higher quality of individuals' economic decisions.

6.2 Future Research

While this study added some pieces to the understanding of subjective LE, the work also raised new questions, which are to be addressed by future research. Two fields are particularly important: First, more empirical evidence is needed to understand what people actually mean when they report a subjective LE. As discussed at several points, it is not really clear whether (1) respondents report an expected value of their LE or the modus, and if (2) they correctly understand the questionnaire and answer what they are asked for, for example the average LE for people of their age (and not their cohort). These issues should be addressed with a detailed survey on subjective LE or by the use of elaborate interviews in a small sample.

Second, it is an open question how the updating model for subjective LE presented here interacts with updating models for subjective survival probabilities. In the same way as Hamermesh (1985) checks basic consistency of subjective LE and subjective survival probabilities, a future step is to analyze if people *update* subjective survival probabilities and subjective LE in a consistent way. From a theoretical point of view, we plan to rewrite the heuristic updating model by basing the updating of subjective LE on estimated probabilities, which allows to parameterize the identified split-up in a Baysian updating framework as in Viscusi (1984).

Appendix A

Results from Sensitivity Analyses

The following tables report regression results from additional regressions as described in the text. Tables A.1 through A.4 repeat the analysis from chapter 4 putting equal weight on all observations. Tables A.5 through A.8 show the results for a dataset, where implausible answers (subjective LE lower than current age) have not been excluded. Finally, tables A.9 and A.10 repeat regressions from chapter 5 including a dummy for the access panel-subsample.

Men: Determinants of Subjective LE (Unweighted Regression)

Variable	I: Subjective LE	II: Effect on Pr(longer)	II: Effect on Pr(not shorter)	IV: Estimated Average LE
General				
Age	**.1370673*** **	**.0039349*** **	**.0040254*** **	.0666737***
	(.0180801)	(.00082)	(.00073)	(.0122822)
Age squared	**.0074007*** **	**.0001407** **	**.0001859*** **	**.0048822*** **
	(.0006694)	(.00003)	(.00003)	(.0005472)
East	**-.6646813* **	-.0223756	-.0022462	**-.6181944** **
	(.3562022)	(.01718)	(.01548)	(.2650959)
Family situation				
Married	-.0961781	-.0275898	**.0488468*** **	-.1955365
	(.4160746)	(.02091)	(.01703)	(.2769533)
Widowed	.5888712	.243198	.0339362	-.4961546
	(.8463983)	(.1606803)	(.0328)	(.6590451)
Children	-.6914973	-.0021703	-.0240855	**-.8036297** **
	(.4533136)	(.02294)	(.01737)	(.3140046)
Practical help	**.6836468** **	.0006744	.0162056	**.5355396*** **
	(.2711007)	(.01399)	(.01177)	(.196324)
Education				
High school (Abitur)	**.8654305** **	**.0648834*** **	**-.0612013*** **	**.7593799** **
	(.4334129)	(.02108)	(.02005)	(.3003161)
College (Hochschule)	.2306389	-.0036254	**.0322815* **	.3806929
	(.4698828)	(.02284)	(.01803)	(.3350313)
Economic situation				
Income	**.2281174* **	-.004197	-.0053082	**.246146** **
	(.1389544)	(.00719)	(.00707)	(.1032733)
Income squared	-.0052164	.0001917	.0003077	**-.0082446** **
	(.005783)	(.00026)	(.00028)	(.0039096)

Table A.1: Regression Results Unweighted (Men)

Retired	-.5243003	-.012226	-.035418	.0412692
	(.5467958)	(.026)	(.02226)	(.3386787)
Current unemployment	**-1.222195***	-.0173406	.0046906	-.6520204
	(.6364939)	(.02729)	(.02402)	(.4498977)
Unemployment history	-.0454379	.0211968	-.0129243	-.23673
	(.3747584)	(.01808)	(.01585)	(.2550914)
Lifestyle and Behavior				
Current smoker	**-1.632349*****	**-.0641934*****	**-.0359844****	**-.867585*****
	(.4129794)	(.01752)	(.01813)	(.2873802)
Ex-smoker	**-.9081469*****	**-.0387409****	-.0157298	**-.3940171***
	(.3401539)	(.01633)	(.01679)	(.240851)
Weekly drinking	.3094951	-.0220192	**.0322474****	.235766
	(.3056721)	(.01469)	(.01331)	(.2160169)
Weekly exercise	.1871198	**.0299296****	**.0244806***	-.1246891
	(.3056721)	(.01404)	(.0131)	(.2059059)
Voluntary work	**-.4737944***	-.003387	-.0010936	**-.3412085***
	(.2778829)	(.01424)	(.01269)	.2059451
Health status				
Bad health	**-3.798882*****	**-.0978579*****	-.2647469***	-.3506972
	(.5450501)	(.01913)	(.03199)	(.3815254)
Long-term health prob.	**-2.762923*****	**-.1048262*****	**-.1347716*****	**-.6638354*****
	(.3248351)	(.01598)	(.0142)	(.2250463)
Controls				
Year effect 2005	-.1079127	.0718275***	.0267656**	-.9649493***
	(.2590772)	(.01605)	(.01251)	(.19674)
Year effect 2006	-.2781992	.0157504	.0215423**	-.7077192***
	(.2150869)	(.01229)	(.0109)	(.1670115)
Constant	78.16611***	–	–	77.32214***
	(.6949766)			(.5291731)

Figures in parenthesis are robust standard errors. ***,** and * represent statistical significance at 1%, 5% and 10% level, respectively.

Table A.2: Regression Results Unweighted (Men) -continued-

Women: Determinants of SLE (Unweighted Regression)

Variable	I: Subjective LE	II: Effect on Pr(longer)	II: Effect on Pr(not shorter)	IV: Estimated Average LE
General				
Age	**.0828767*** **	**.0030115*** **	**.0017965*** **	**.0283287*** **
	(.0133553)	(.00057)	(.00061)	(.0102894)
Age squared	**.0046519*** **	**.0000824*** **	**.0001209*** **	**.0025861*** **
	(.0006528)	(.00003)	(.00003)	(.0005048)
East	-.4502587	.0040095	-.0003856	**-.6411892** **
	(.3356985)	(.01441)	(.01356)	(.2582352)
Family situation				
Married	-.6004872	**-.0602007*** **	.0024203	-.3212943
	(.3793452)	(.01596)	(.01495)	(.2844756)
Widowed	-.308539	-.0113915	.0033067	-.3448593
	(.4936888)	(.01992)	(.02204)	(.3815327)
Children	-.0826248	-.0000615	.0171387	**-.5240323***
	(.4030136)	(.017)	(.01687)	(.315644)
Practical help	-.2771013	.0026665	**-.0188514***	.0037227
	(.2593873)	(.01137)	(.01134)	(.2073759)
Education				
High school (Abitur)	.5482609	**.0416974** **	-.022422	.4501216
	(.419143)	(.01763)	(.01946)	(.3012323)
College (Hochschule)	.6656705	.0125025	-.0118834	**.8575095** **
	(.493367)	(.02037)	(.02174)	(.3440487)
Economic situation				
Income	**.4547582*** **	**.0179488***	**.0110348** **	**.2739975*** **
	(.1231056)	(.00936)	(.00555)	(.1021644)
Income squared	**-.0160041*** **	**-.0013175***	-.0005722***	-.0059235
	(.0044158)	(.00077)	(.0002)	(.0041781)

Table A.3: Regression Results Unweighted (Women)

Retired	-.6090641	**-.0372492****	-.0484161**	.2261673
	(.4135245)	(.01724)	(.01965)	(.2822265)
Current unemployment	.6317584	.0199949	.0131278	.2126265
	(.4859361)	(.02271)	(.01739)	(.3812125)
Unemployment history	**-.9295226*****	.000534	**-.0258699***	**-.4172806***
	(.32446)	(.01407)	(.01366)	(.252786)
Lifestyle and Behavior				
Current smoker	**-1.560756*****	**-.0298775****	**-.0306412***	**-1.254041*****
	(.3723036)	(.01415)	(.01599)	(.2892196)
Ex-smoker	**-.6283424***	-.0137106	-.0219297	-.1118814
	(.3424904)	(.01387)	(.01601)	(.2647754)
Weekly drinking	**.9054049*****	.012898	.0129177	**.6284686*****
	(.2808842)	(.01249)	(.01264)	.218222
Weekly exercise	.1599274	**.0196145***	-.0025782	-.0958564
	(.2621911)	(.01168)	(.0113)	(.2006791)
Voluntary work	.2801611	-.0098914	.0010903	**.4501247****
	(.2605772)	(.0116)	(.01161)	(.1999405)
Health status				
Bad health	**-3.884172*****	**-.0755267*****	**-.1950286*****	-.2194916
	(.5456886)	(.01491)	(.02945)	(.3680408)
Long-term health prob.	**-2.465588*****	**-.0858544*****	**-.1332877*****	**-.5054893****
	(.2898606)	(.01217)	(.01383)	(.2217764)
Controls				
Year effect 2005	.1374084	.0550103***	-.0168734	-.2262156
	(.2568509)	(.01357)	(.01323)	(.2112348)
Year effect 2006	-.56982***	.0080449	.0048569	-.6461321***
	(.1954921)	(.01071)	(.01023)	(.1650587)
Constant	81.43103***	–	–	81.14939***
	(.6258149)			.4926883

Figures in parenthesis are robust standard errors. ***,** and * represent statistical significance at 1%, 5% and 10% level, respectively.

Table A.4: Regression Results Unweighted (Women) -continued-

Men: Determinants of Subjective LE (Including Implausible Answers)

Variable	**I: Subjective LE**	**II: Effect on Pr(longer)**	**II: Effect on Pr(not shorter)**	**IV: Estimated Average LE**
General				
Age	**.0498698****	**.0024152*****	**.0014626***	.011353
	(.0207527)	(.00085)	(.00088)	(.0153426)
Age squared	**.0064801*****	**.0001248*****	**.00017*****	**.0041256*****
	(.0008404)	(.00004)	(.00004)	(.0006608)
East	-.4515118	.0006698	.0216427	**-.7437163****
	(.4324625)	(.01976)	(.01752)	(.3302309)
Family situation				
Married	-.0713665	-.0132854	**.0415139****	-.2283854
	(.4901351)	(.02263)	(.01907)	(.3232207)
Widowed	.7208537	.0637352	.0474386	-.3275952
	(.9978609)	(.05389)	(.03669)	(.6850669)
Children	-.597577	-.0005788	-.0231257	**-.8949342****
	(.5416038)	(.02484)	(.0199)	(.3747274)
Practical help	**.7273563****	-.0095288	**.0237476***	**.6510973*****
	(.3500523)	(.01642)	(.01463)	(.2504101)
Education				
High school (Abitur)	**1.075694****	**.0648068*****	**-.0701648*****	**.8433887****
	(.5508046)	(.02329)	(.0257)	(.4051096)
College (Hochschule)	.3951865	-.0201276	.0293187	**.7979836***
	(.5970498)	(.02378)	(.0223)	(.449212)
Economic situation				
Income	.1618167	-.0080405	-.0001592	.1947266
	(.162515)	(.00788)	(.00915)	(.1262083)
Income squared	-.0029871	.00031	.0003731	-.0066453
	(.0058605)	(.00028)	(.0005)	(.0041338)

Table A.5: Regression Results Including Implausible Answers (Men)

Retired	.2329796	-.0069585	-.0188425	.4948303
	(.6710791)	(.02955)	(.02819)	(.4079725)
Current unemployment	**-1.424078****	-.0385728	.0010239	-.6774973
	(.697302)	(.02833)	(.02827)	(.5159436)
Unemployment history	.0969295	.0176765	-.018621	.0022332
	(.4645124)	(.02103)	(.01859)	(.3318686)
Lifestyle and Behavior				
Current smoker	**-2.201193*****	**-.0645125*****	**-.0610468*****	**-1.174101*****
	(.4991318)	(.0193)	(.02257)	(.3644713)
Ex-smoker	**-1.138475*****	**-.0504557*****	-.0262064	**-.4966497***
	(.4039346)	(.0176)	(.02024)	(.3040676)
Weekly drinking	.5033534	-.0256915	**.039999****	.3273468
	(.3698008)	(.01641)	(.01615)	(.2775427)
Weekly exercise	.4557604	**.0380518****	.0258949	-.0090061
	(.3639569)	(.01599)	(.01615)	(.2740021)
Voluntary work	**-.7663239****	.003757	-.0025039	**-.6041803****
	(.3593888)	(.01593)	(.01496)	(.2638649)
Health status				
Bad health	**-4.693616*****	**-.0917965*****	**-.2593526*****	**-1.063915***
	(.7706294)	(.02095)	(.03848)	(.5745738)
Long-term health prob.	**-2.670732*****	**-.0961512*****	**-.1382222*****	-.3431116
	(.4161944)	(.01785)	(.01894)	(.2879831)
Controls				
Year effect 2005	-.0449346	.0688478***	.0256084*	-.9216082***
	(.2854609)	(.01594)	(.01362)	(.2199342)
Year effect 2006	-.3008668	.026333*	.0319688**	-.9288975***
	(.3207214)	(.01521)	(.01373)	(.2463218)
Constant	77.62562***	–	–	77.24047***
	(.8168836)			(.6384993)

Figures in parenthesis are robust standard errors. ***,** and * represent statistical significance at 1%, 5% and 10% level, respectively.

Table A.6: Regression Results Including Implausible Answers (Men) -continued-

Women: Determinants of SLE (Including Implausible Answers)

Variable	I: Subjective LE	II: Effect on Pr(longer)	II: Effect on Pr(not shorter)	IV: Estimated Average LE
General				
Age	**.039149****	**.0021998*****	.0004262	.0016937
	(.019888)	(.00061)	(.00074)	(.01617)
Age squared	**.0046531*****	**.0000739*****	**.0001403*****	**.0021561*****
	(.0008909)	(.00003)	(.00003)	(.000742)
East	-.3036604	-.0007339	.0138685	**-.5701446***
	(0.457)	(.01513)	(.015)	(0.077)
Family situation				
Married	-.1219419	**-.0483357*****	.0069339	.0167714
	(.4357751)	(.01607)	(.01648)	(.3446811)
Widowed	.143949	.0030937	-.0013687	.0328427
	(.6927093)	(.02057)	(.02586)	(.5644275)
Children	-.4158634	-.0039901	.0118961	**-.8098626****
	(.4908833)	(.01812)	(.01968)	(.3905141)
Practical help	**-.5595906***	-.0008295	**-.0264272****	-.1378086
	(.3354113)	(.01189)	(.01314)	(.2797078)
Education				
High school (Abitur)	.5563627	.0268873	-.0378846	**.7842124****
	(.4937165)	(.0171)	(.02394)	(.3751461)
College (Hochschule)	.8385807	.0193031	-.0106281	**.8771828****
	(.5656265)	(.02144)	(.02627)	(.4133928)
Economic situation				
Income	**.5656265*****	**.0199393***	**.0193907****	**.2055086***
	(.1497913)	(.01058)	(.00794)	(.1217492)
Income squared	**-.0173517*****	**-.0015464***	**-.0009178****	-.0038436
	(.0054325)	(.00083)	(.00041)	(.0044454)

Table A.7: Regression Results Including Implausible Answers (Women)

Retired	-.3874641	**-.0348642****	**-.0444911***	.677524
	(.6590699)	(.0182)	(.02399)	(.5034067)
Current unemployment	.5974661	.0052185	.0109479	.2869141
	(.594693)	(.02103)	(.02118)	(.4747147)
Unemployment history	**-.8526848****	-.0019896	-.024124	-.3536811
	(.3999995)	(.01465)	(.01563)	(.3183563)
Lifestyle and Behavior				
Current smoker	**-1.795849*****	-.0247028	**-.0449346****	**-1.396124*****
	(.448064)	(.01539)	(.01875)	(.3525118)
Ex-smoker	-.5538815	-.0155823	**-.0339683***	.1440914
	(.4107903)	(.01461)	(.01993)	(.3230234)
Weekly drinking	**1.045149*****	.0100935	.0148571	**.7214336*****
	(.3377372)	(.0136)	(.01465)	(.2641227)
Weekly exercise	.2828429	.0176776	-.0144701	.0622069
	(.3396919)	(.01233)	(.01346)	(.2683958)
Voluntary work	.3162585	-.017559	.0173207	.3466551
	(.3417478)	(.01258)	(.01412)	(.2713481)
Health status				
Bad health	**-4.631726*****	**-.0893769*****	**-.2075288*****	-.5473615
	(.7408451)	(.01144)	(.0355)	(.5096213)
Long-term health prob.	**-2.463629*****	**-.0626618*****	**-.1333163*****	**-.5727781****
	(.350563)	(.01257)	(.01577)	(.2830089)
Controls				
Year effect 2005	.1030561	.0555194***	-.015355	-.2873231
	(.2930221)	(.01333)	(.01419)	(.2468023)
Year effect 2006	-.6089763**	.0011108	.0113522	-.7086169***
	(.262918)	(.01194)	(.01223)	(.220556)
Constant	81.03485***	–	–	81.10066***
	(.7199113)			(.5733142)

Figures in parenthesis are robust standard errors. ***,** and * represent statistical significance at 1%, 5% and 10% level, respectively.

Table A.8: Regression Results Including Implausible Answers (Women) -continued-

Influence on LE Adjustments with Access Panel- Dummy (Men)

	Adj_SLE		Adj_EstAvr	
	I	II	I	II
Negative health shock (β)	**-.945****		-.296	
	(.460)		(.348)	
Chronic health shock (β)		**-1.59*****		-.314
		(.537)		(.446)
Age (α_1)	.00483	-.00204	.00803	.00305
	(.0101)	(.00840)	(.00829)	(.00719)
Constant (α_0)	**.958*****	**.907*****	**1.26*****	**1.18*****
	(.324)	(.258)	(.254)	(.207)
Access Panel	-.615**	-.535**	-.536**	-.477**
	(.311)	(.269)	(.237)	(.212)
Year dummy 2006	-.920**	-.932**	-.868***	-.825***
	(.386)	(.366)	(.310)	(.291)

Figures in parenthesis are robust standard errors. ***,** and * represent statistical significance at 1%, 5% and 10% level, respectively.

Table A.9: Regression Results Updating with Access Panel-Dummy (Men)

Influence on LE Adjustments with Access Panel- Dummy (Women)

	Adj_SLE		Adj_EstAvr	
	I	II	I	II
Negative health shock (β)	-.667		-.316	
	(.434)		(.371)	
Chronic health shock (β)		**-1.74*** **		-.329
		(.514)		(.409)
Age (α_1)	**.020***	**.0150***	**.0196****	**.0178****
	(.0101)	(.00896)	(.00888)	(.00782)
Constant (α_0)	.240	**.450***	**.527****	**.483****
	(.301)	(.260)	(.253)	(.220)
Access Panel	.282	.344	.0540	.197
	(.341)	(.303)	(.298)	(.265)
Year dummy 2006	-.615	-.790**	-1.01***	-1.01***
	(.414)	(.398)	(.339)	(.334)

Figures in parenthesis are robust standard errors. ***,** and * represent statistical significance at 1%, 5% and 10% level, respectively.

Table A.10: Regression Results Updating with Access Panel-Dummy (Women)

Appendix B

Questions on Subjective LE

We provide an excerpt from the SAVE survey containing the exact wording of all questions concerning life expectancies. The full survey can be found in Börsch-Supan, Coppola, Essig, Eymann, and Schunk (2008).

1. What average age do you believe men/women of your age will reach?
- Men (Year:)
- Woman (Year:)

2. If you think of your own situation and your state of health, do you think that, in comparison to other men/women of your age group, your lifespan will be ...
- Shorter? (Continue with 3a)
- Approximately as long as the average? (Done)
- Longer? (Continue with 3b)

3a. By how many years?
- (Number of years:) (Continue with 4a)

3b. By how many years?
- (Number of years:) (Continue with 4b)

4a. Why don't you think you will live as long as the average?
- Because of existing illnesses or disability
- Because of your lifestyle
- Because of the death at a young age of close relatives
- For other reasons (specify)

4b. Why do you think you will live longer than average?
- Because of your good state of health
- Because of your lifestyle
- Because of the old age of close relatives
- For other reasons (specify)

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mea
Mannheimer Forschungsinstitut
Ökonomie und demografischer Wandel

L13, 17
Universität Mannheim
68131 Mannheim

Tel 0621 - 181 18 62
Fax 0621 - 181 18 63

info mea.uni-mannheim.de
www.mea.uni-mannheim.de