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Essays on Subjective Survival Probabilities, Consumption, and Retirement Decisions

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Essays on Subjective Survival Probabilities, Consumption, and Retirement Decisions

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Essays on Subjective Survival Probabilities, Consumption, and Retirement Decisions

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en pensioneringsbeslissingen

(met een samenvatting in het Nederlands)

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To my parents

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Vesile Kutlu Koç

Munich, November 2014

Contents

List of Tables

List of Figures

Chapter 1

Introduction

The social security budgets of many industrialized countries are under strain due to population aging. Since the 1980s, life expectancy in those countries has increased significantly due to the improved health care facilities. For example, in 1980 the life expectancy at birth in United States was 73.74 years and the life expectancy at birth in the Netherlands was 75.77 years. In 2010, life expectancy at birth in the United States and the Netherlands has increased to 78.83 years and 80.66 years, respectively.[1] Recent pension reforms in industrialized countries are, in part, motivated by the increased life expectancy. The Dutch government decided to increase the statutory retirement age from 65 to 66 years in 2019 and to 67 years in 2023. The Dutch government also introduced a flexible retirement program to keep older workers in the labor force and prevent early exits from the labor market. Similar reforms were introduced in the United States as well. Moreover, the employer-sponsored pension benefits in the United States have been less generous over the last years. For example, many employers in the United States have been switching from defined benefit (DB) to defined contribution (DC) plans. In the DB pension plan employees receive a fixed annual amount during their retirement and this amount is determined by their age, years of service and salary. In the DC pension plan employees contribute a fixed amount in each year and these contributions are invested, for example, in the stock market. The pension income under the DC plan is determined by the return on the investments which can be positive or negative. Therefore, DC plan holders may face greater uncertainty regarding their retirement benefits compared to DB plan holders. All of these developments show that the pensioners face a greater uncertainty about their pension benefits nowadays than they did in the past. The proposed pension reforms demand that individuals take more responsibility to financially prepare for retirement in an environment of increasing economic uncertainty.

The four essays in this thesis cover a range of topics including individuals' life expectancy and their actual mortality risk, consumption decisions of the elderly, retirement behavior, and retirement savings. As individuals are expected to take more responsibility in

[1] Source: Human Mortality Database

their retirement planning and savings decisions, it is important to understand whether they are aware of improvements in life expectancy. Therefore, Chapter 2 investigates the extent to which individuals' beliefs about their own life expectancy coincide with the realizations. In household surveys, individual life expectancy is usually measured with questions about the probability of survival to a target age. If subjective survival probabilities (SSPs) are accurate predictors of individuals' actual survival, we can be more confident that individuals can assess their survival chances accurately and, therefore, can make more optimal economic decisions. To compare individuals' survival probabilities with their actual mortality risk, I use data from the DNB Household Survey (DHS) supplemented with (administrative) data on actual mortality from the causes of death registry.

One of the main findings of the second chapter is that when I control for income and education level, SSPs predict observed mortality within the sample, but when I control for self-rated health status and smoking behavior, the correlation disappears. This outcome may suggest that SSPs' predictive power—being largely determined by the (observed) current health situation with little additional information on expected future health events—is rather limited. I also show that, Dutch men and women underestimate, on average, their remaining life duration by about 1 and 8 years, respectively.

Underestimation of survival probabilities by the Dutch may have economic implications if individuals base their decisions on them. For example, those who think that they will not live until old age may not save enough to finance consumption during retirement. Therefore, in Chapter 3 I focus on the reasons for underestimation of life expectancy. In particular, I investigate if the underestimation of life expectancy by the Dutch can perhaps be partly explained by their insufficient knowledge on population life expectancy. The third chapter is, therefore, an extension of the second chapter. I measure the respondent's knowledge on population statistics using questions about the average life expectancy in the Netherlands in the DNB household survey and I compare individuals' beliefs about population life expectancy with the population life expectancies from the age and gender specific period life tables. This comparison reveals the extent to which individuals' knowledge on the population life expectancy is in line with the actual life expectancy in the population.

The main finding of the third chapter is that the Dutch's underestimation of population life expectancy significantly explains the underestimation of their remaining lifetime. The role of knowledge on population life expectancy in being able to answer the probabilistic survival questions accurately is large: a one-year more accurate prediction of population life expectancy is, on average, associated with about half a year more accurate prediction of one's own life expectancy. This finding suggests that if individuals were better informed about population life expectancies, the accuracy of their survival beliefs could improve considerably. As a result, a policy of providing respondents information about population life expectancies may help them making more optimal economic decisions such as saving and retirement decisions.

Chapter 4 investigates whether individuals use their subjective probabilities of survival when they make economic decisions. In particular, I focus on the role of SSPs in explaining the consumption decisions of the elderly. A simple life cycle model without uncertainty predicts that rational agents' level of consumption is determined by their lifetime income. Under the assumption that individuals' annual earned income is greater than their annual retirement income, this model implies that individuals save when they are young and draw down their assets after retirement. Previous studies find no evidence in favor of wealth decumulation by the elderly even at advanced ages. Extended versions of the life cycle model make attempts to explain this inconsistency. Hurd (1989, 1999) explains saving behavior of elderly singles and couples by adding uncertainty about the date of death and bequest motives. The fourth chapter tests the predictions of the models proposed by Hurd (1989, 1999) for elderly Americans. For this purpose I use data taken from the Health and Retirement Study (HRS) supplemented with the Consumption and Activities Mail Survey (CAMS).

One of the main findings of the fourth chapter is that more than half of the individuals in the sample spend more than their annuity income after retirement which indicates most individuals have decreasing wealth profiles in old age as predicted by the theory. Moreover, I find that the difference between total consumption and annuity income increases with the level of wealth for both elderly singles and couples. The findings regarding the role of SSPs in explaining consumption decisions in old age indicate that consumption growth decreases with higher subjective mortality rates for elderly singles. On the other hand, the growth rate of consumption of elderly couples does not depend on their subjective mortality risk, contrary to the prediction of the theory. One of the reasons behind this finding can be that the assumption of the model regarding the same coefficient of relative risk aversion for both spouses may not be supported by the empirical evidence since women tend to be more risk averse than men in financial decision-making. Overall, the fourth chapter finds some evidence in favor of wealth decumulation by the elderly after retirement.

Chapter 5 investigates the drop in consumption at retirement, i.e. the so-called retirement-consumption puzzle. Looking at consumption change at retirement might help to understand whether individuals have saved enough for their retirement. The pension reforms in many industrialized countries include reductions in public pensions which require individuals to save more for their retirement. If individuals are forced to reduce their spending at retirement, this may suggest that they have not saved enough for retirement. In this case the reforms aiming to reduce public pensions might be ill-advised.

Earlier research in this field maintains the assumption that retirement is an "absorbing state" which means that re-entering the labor force after being retired is not possible. Unretirement is defined as returning to the labor force after retirement and has become more popular in some countries in recent decades. (Maestas, 2010; Petersson, 2011; Kanabar 2012). For example, Maestas (2010) shows that at least 26 percent of Americans re-enter the labor force following a retirement spell. Focusing on consumption drop at retirement only may be misleading while unretirement among retirees is so prevalent. For example, those who retired earlier than expected due to unemployment may experience a negative income shock at retirement and therefore may choose to re-enter the labor force to finance their consumption during unretirement. In the fifth chapter I investigate consumption behavior of retirees also after they re-enter the labor force. For this purpose I use nine waves of the Health and Retirement Study (HRS) which represents the population of Americans over age 50 and their spouses.

The fifth chapter has several important findings. The unretirement decision is mainly determined by pre-retirement expectations of work and financial factors such as the amount of individuals' accumulated savings at the time of retirement and having an occupational pension plan. In contrast with the earlier studies in the literature, I do not find a significant drop in food consumption at retirement when retirement is fully anticipated. On the other hand, household food consumption decreases by about 7 percent when women become retired expectedly or unexpectedly. A significant drop in household food consumption at the women's retirement can be explained by women's contribution to home production. Another finding of the fifth chapter is that in line with the predictions of the life-cycle model consumption does not respond to unretirement if it is fully anticipated. One of the reasons for this finding could be that post-retirement jobs pay much less than pre-retirement jobs and therefore individuals' income does not increase significantly when they unretire. Overall, the findings of the fifth chapter suggest that individuals have saved enough to smooth their consumption around retirement, on average.

In summary, this thesis concludes that the Dutch underestimate their life expectancy, on average. This finding is important from a policy perspective since the underestimation of life expectancy may lead to insufficient retirement savings and early retirement. On the other hand, the finding that having knowledge on population life expectancy significantly improves the answers given to subjective survival probabilities suggests that the problem of underestimation can be overcome by informing the Dutch public about the population life expectancy. The recent pension reforms such as increasing the legal retirement age and introducing flexible retirement programs aim to keep older worker in the labor force. This thesis shows that to increase the effectiveness of these pension reforms the Dutch government can inform the public about population life expectancy. Such a policy may help individuals understand that they live longer than they expected and assess their survival chances more accurately. As a result, individuals may choose to delay retirement or increase their savings to finance their consumption during retirement.

This thesis also concludes that there is some evidence in favor of wealth decumulation by elderly Americans after retirement. As predicted by the theory, the subjective survival probabilities explain individuals' consumption decisions at old age. The mortality risk increases with age, therefore, individuals increase current consumption at the expense of future consumption. This finding is in line with the findings of the previous two chapters in the sense that individuals make economic decisions based on their survival expectations and, therefore, informing individuals about population life expectancy may help them make more optimal decisions. On the other hand, the finding that subjective survival probabilities do not explain couples' consumption decisions deserves further analysis. The assumption of the theoretical model regarding the same risk preferences for men and women may not hold in real life. For instance, one can account for the fact that women are in general more risk averse compared to men. A richer model can capture the relationship between mortality risk and consumption decisions of elderly couples.

Finally, this thesis also concludes that moving back to labor force after retirement is very common among older Americans and most of the unretirement transitions are anticipated before retirement. On the other hand, the fact that the amount of individuals' accumulated savings at the time of retirement also plays a role in the decision of unretirement suggests that arrival of new information after retirement regarding financial situation may cause individuals to update their expectations of work during retirement. For example, unretirement is more common among the DC plan holders compared to the DB plan holders probably because the pension income under the DC plan is exposed to financial market risks. The shift from DB plans to DC plans is likely to continue in the future, and therefore unretirement is likely to become more prevalent. The finding that individuals do not change their consumption around retirement is very promising as it shows that, on average, individuals are forward-looking and they have saved to smooth their consumption around retirement.

Chapter 2

Individuals' Survival Expectations and Actual Mortality[2]

2.1 Introduction

Individual life expectancy plays an important role in life cycle models of economic behavior. Several household surveys, therefore, include probabilistic questions (Manski 2004) to collect information on individuals' beliefs about their survival chances to one or two target ages (Hurd 2009). Most particularly, the existing literature indicates that these subjective survival probabilities (SSPs) elicited from survey respondents convey useful information about their actual life duration. This observation has an important practical implication for economic research. If SSPs are accurate predictors of individuals' actual survival, they can be used as measures of individual mortality risk in economic models, including life-cycle models of saving, consumption, and retirement behavior.[3,4] Yet, earlier research indicates that life-cycle models, which replace individual mortality risk with that from (actuarial) life tables, cannot explain certain well-known anomalies in the data (Hurd and McGarry 2002). SSPs may shed light on this issue as they convey information on individuals' beliefs about survival, which can differ from actuarial survival probabilities. For instance, the anomaly of insufficient preretirement savings to finance retirement consumption can in part be explained by models that use SSPs. If prior to retirement, individuals systematically underestimate their remaining life duration, hence their beliefs about survival are lower than their actual survival to a certain age, their savings level will be lower than that implied by a life-cycle model of consumption based on actuarial survival probabilities. In fact, Gan *et al.* (2004) and Salm (2010) show that individuals have private information about their own mortality risk on which they base their economic decisions. Our paper focuses on the step that needs to be taken before developing and estimating economic models that incorporate SSPs, and explores the extent to which individuals'

[2] This chapter is a joint work with Adriaan Kalwij.

[3] Individual mortality risk is the risk associated with the uncertainty of an individual's remaining lifetime conditional on given survival probabilities (De Waegenaere *et al.* 2010).

[4] Also, in this case, studies investigating the socio-economic gradient in mortality may use SSPs as substitutes for actual mortality data (Delavande and Rohwedder 2011).

beliefs about survival (SSPs) relate to their actual mortality and how this differs with socioeconomic status and health characteristics.

The contribution to the literature of our paper is threefold. First, we investigate whether (remaining) life expectancy of the Dutch measured by their SSPs correlate with actual mortality risk and assess its predictive power. We compute subjective remaining lifetime using two SSPs for each individual. Second, by estimating subjective and objective mortality risk models, we analyze the extent to which individuals' SSPs contain well-known differences in mortality risk with respect to socioeconomic and health status, and behavioral risk indicators such as smoking and drinking. Methodologically, by assuming a Gompertz model, we can estimate the same parameters of a mortality risk model using both subjective and objective survival information. Finally, we use the estimation results to quantify the gap between individuals' subjective life expectancy and the life duration implied by observed mortality for different types of individuals. For this purpose, we use data from the DNB Household Survey (DHS) supplemented with (administrative) data on actual mortality from the causes of death registry.

The empirical literature on this topic can be divided into two categories: The first investigates the link between SSPs and actuarial survival probabilities (Hamermesh 1985; Hurd and McGarry 1995; O'Donnell *et al.* 2008; Perozek 2008; Peracchi and Perotti 2011; Teppa 2012). The second assesses the relation between SSPs and actual (objective) mortality and whether SSPs can predict actual mortality within the sample (Van Doorn and Kasl 1998; Smith *et al.* 2001; Hurd and McGarry 2002; Siegel *et al.* 2003; Peracchi and Perotti 2011). The research findings in the first stream suggest that males overestimate while females underestimate their survival probabilities compared to life table survival probabilities, although males tend to assess their life expectancy better than females. Nonetheless, Teppa (2012), using Dutch data, finds that both Dutch males and females have, on average, lower SSPs relative to actuarial survival probabilities. The main finding of the second stream is that individuals who expect to live longer are less likely to die. Hurd and McGarry (2002), for instance, report that an increase in the subjective survival probability from 0 to 1 reduces the mortality rate by 53 percent.[5]

Most of the above studies, however, tend to estimate models in which actual mortality is explained by the subjective probability of survival up to age 75, together with such other mortality determinants as income, wealth, education, smoking, and health indicators. One

[5] See also Van Doorn and Kasl (1998) and Siegel *et al.* (2003).

notable exception is Perozek (2008), a study closely related to ours, which fits subjective survival functions using the two SSPs available for each respondent in the HRS survey to generate subjective cohort tables for males and females.[6] In contrast with Perozek (2008), we use subjective survival information to estimate the parameters of a mortality risk model that we also estimate using actual mortality information. We are thus able to assess whether the socioeconomic status and health-related parameters estimated using the subjective data are close to those obtained using actual mortality data.

A second study that is directly linked to ours is Delavande and Rohwedder (2011), which compares the coefficient estimates of an actual survival model with those implied within the same sample by a subjective survival model. The findings suggest that Americans' actual mortality and subjective survival expectations are similarly associated with wealth, income, and education, which implies that in the case of the United States, SSPs are informative proxies for actual survival. This study, however, examines survival only up to age 75, whereas our sample includes respondents aged 75 or older. More importantly, when comparing actual survival with subjective survival, we control for socioeconomic variables as well as health indicators. Furthermore, unlike Delavande and Rohwedder (2011) which adds age dummies to control for respondents' baseline age, we use two SSPs for each respondent which, together with the assumption of a Gompertz hazard function, allows us to estimate the age gradient in subjective mortality risk.

One of the main findings in our paper is that when we control for income and education level, SSPs predict observed mortality within the sample, but when we control for self-rated health status and smoking behavior, the correlation disappears. This outcome may suggest that SSPs' predictive power—being largely determined by the (observed) current health situation with little additional information on expected future health events—is rather limited. We also show that, men and women underestimate, on average, their remaining life duration by about 1 and 8 years, respectively, meaning that their long-term decisions on such factors as retirement and savings may be suboptimal. The association of current health status with subjective survival is less strong than with objective survival and individuals underestimate the risks from smoking.

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[6] This U.S. study investigates whether the Social Security Actuary's (SSA) revision to the gender gap in longevity can be predicted by the gender gap implied by the subjective cohort life tables. Its main finding is that subjective cohort tables predict a smaller difference in life expectancy between men and women than do the SSA predictions. This relatively small gender gap in longevity results from the systematic overestimation of the mortality risk by women relative to men.

The paper is structured as follows: Section 2.2 describes the data. Section 2.3 outlines the mortality risk model and the methods for its estimation using objective (actual) and then subjective survival data. Section 2.4 presents the estimation results, and Section 2.5 offers our concluding remarks.

2.2 Data

To compare Dutch individuals' survival expectations with their actual mortality (i.e., date of death), this paper combines survey data with individual-level administrative data. The SSPs (subjective survival probabilities) are taken from the 1995 and 1996 waves of the DNB Household Survey (DHS), begun in 1993 and originally known as the CentER Savings Survey. The DHS database, compiled using an Internet survey of around 2,550 Dutch households, includes detailed information on respondents' age, income, health, education, labor market status, assets and liabilities, and psychological state (see Alessie *et al.* 2002 for a detailed description). All of the DHS questions are asked of two different panels, one a nationwide representative panel of around 1,900 households and the other, a high-income panel of around 650 households that represent the top 10 percent of the income distribution. Every year, all household members aged 16 or over are interviewed online. Those who do not have a computer and/or Internet access are provided with these tools by the survey agency.

The data on the actual mortality of survey respondents are obtained from the Dutch causes of death registry (DO, DoodsOorzaken) survey, which records the date of death of all residents deceased during the 1995–2010 period. These data are provided by medical examiners, who are legally obliged to submit them to Statistics Netherlands. The DO dataset also assigns a personal identifier that matches the personal identifier in the DHS, thereby allowing determination of whether individuals in the 1995 or 1996 wave of the DHS were still alive at the end of the observation period (December 31, 2010) or whether they had died, and if so, on which date.

The DHS measures subjective survival probabilities using the following survey question:

- *How big do you think is the chance that you will attain (at least) the age of T?*

where T ∈ {75, 80, 85, 90, 95, 100} is a target age that depends on the respondent's current age.[7]

Respondents aged 25 through 65 report their probability of survival to age 75 and age 80; those aged 65 through 70, their survival expectations to age 80 and age 85; and respondents aged 70–75, 75–80, and 80–85, their expected survival probabilities to 85 and 90, 90 and 95, 95 and 100, respectively (see Table 2.1). The responses are measured on a 10-point scale, from 0, "no chance at all," to 10, "absolutely certain." Following Hurd and McGarry (1995), we assume that after being divided by 10, the responses can be interpreted as probabilities conditional on being alive at a certain age.[8] To construct our main variable of interest, median remaining life duration, we use two survival probabilities for each individual (see Section 2.2.2.1).

2.2.1 Sample Selection

We include in our sample individuals aged 25 and over.[9] The DHS sample, which is cross-sectional, consists of one observation per individual in either 1995 or 1996. If respondents were observed in both the 1995 and 1996 waves, we use only the earlier response to avoid the potential influence of repeated interviewing on respondent behavior (Lazarsfeld 1940; Sturgis *et al.* 2009); for example, respondents asked about survival probability in 1995 may seek more information about their survival chances before responding in 1996. Our method eliminates the risk of possible learning effects.

Manski (2004) suggests that "showing that respondents are willing and able to respond to probabilistic questions is an obvious prerequisite for substantive interpretation of the data" (p. 1342). Table 2.1 lists the SSP response rates, which in our sample, total an average of 86.35 percent, a considerably lower response rate than in the HRS (about 98

[7] The framing of the question may affect respondents' answers to SSPs. For instance, respondents might have provided different answers if they had been asked "*How big do you think is the chance that you will attain (at most) the age of T*?" Whereas the actual survey question asks individuals' probability of living to a certain age or older, the latter asks their chance of dying by a certain age and younger. Payne *et al.* (2013) find that individuals report higher SSPs in the first than in the second.

[8] For computational reasons (see section 2.A), we replace probabilities 0 and 1 with 0.01 and 0.99, respectively.

[9] Because many individuals under 25 are still enrolled in education, their individual income and (final) educational level are unavailable. We run a robustness test by using a different age group (a sample of individuals older than 50) and our main results are to a large extent unchanged (see section 2.D).

percent) or SHARE (about 90 percent) surveys (Hurd and McGarry 1995; Peracchi and Perotti 2011).

Table 2.1: Response Rates to Survival Probabilities

Age of respondent	Survival probabilities	Number of respondents asked the probability questions	Number of respondents who actually answered the probability questions	Response rate (%)
16-65	P75 and P80	5,130	4,427	86.296
65-70	P80 and P85	307	267	86.971
70-75	P85 and P90	186	158	84.946
75-80	P90 and P95	83	74	89.157
80-85	P95 and P100	32	27	84.375

Notes: N = 5,738. Nine observations were excluded from the analysis for being in the 85+ age category, for which we do not observe the two survival probabilities.

A relatively easy way to assess respondents' understanding of the survival probability questions is to check whether they can provide internally consistent answers. For example, if a respondent says that his survival probability to age 75 is less than or equal to his survival probability to age 80, his answer violates the strict monotonicity assumption. In fact, his survival probability to age 75 should be greater than his survival probability to age 80 because to reach age 80, he must first survive until age 75. There is also a risk of mortality between these two ages.

Table 2.2: Inconsistency Rates to Survival Probabilities

Probability comparison	Number of respondents	% of respondents
Prob($t_{1,i}$)<Prob($t_{2,i}$)	31	0.626
Prob($t_{1,i}$)=Prob($t_{2,i}$)	1,590	32.102
Prob($t_{1,i}$)>Prob($t_{2,i}$)	3,332	67.272

Notes: $t_{1,i}$ and $t_{2,i}$ are two different target ages, where $t_{1,i} < t_{2,i}$; 4,953 individuals out of 5,747 reported both Prob($t_{1,i}$) and Prob($t_{2,i}$).

As Table 2.2 shows, about 67 percent of respondents provided answers that satisfy the strict monotonicity assumption. Around 32 percent reported equal survival probabilities for two target ages, while about 0.63 percent indicated a survival chance to the earlier target age that is less than their survival chance to the later target age. Perozek (2008) suggests that respondents with equal survival probabilities can still give valuable information about the shape of individual subjective survivor functions. Respondents who provide equal survival probabilities for two target ages might, for example, be rounding out their true survival probabilities to the nearest tenth because the answer to survival probability questions ranges from 0 to 10. However, the inclusion of equal survival probabilities in the estimation necessitates arbitrary assumptions and we therefore exclude these 32.73 percent with inconsistent answers from our analysis. Only as a sensitivity check, we have included respondents with equal probabilities in our sample and assume a 5 percent shift between equal probabilities (see Tables 2.C.1–2.C.2 in section 2.C). For brevity, we do not detail these additional results, but in general it can be concluded that they are sensitive to the inclusion of equal survival probabilities in the estimation.[10] Finally, there is also a tendency for respondents to provide focal point answers on SSPs (i.e., clustered around 0, 0.5, and 1; see Table 2.B.1, section 2.B). In the face of Kleinjans and van Soest's (2013) evidence that taking into account rounding or focal point answers does not substantially change the coefficient estimates on the determinants of subjective probabilities of survival, we make no corresponding corrections to the SSP responses.

In sum, at baseline, the sample includes 5,747 observations and we are forced to drop 2,688 observations (46.8 percent of the initial sample) either because the strict monotonicity assumption for SSP responses is violated or because information is missing for one of the covariates under study. Although we are solely concerned with within sample predictions, we test if individuals included in our final sample (3,059 individuals and 10.8 percent of whom were deceased by December 2010) have the same mortality risk as those dropped from the baseline sample. We find no significantly different mortality risk (at p = 0.102), indicating that the sample selection is not endogenous with respect to mortality. The construction of our median remaining life duration variable is detailed in the next section; the definitions of our other variables are given in Table 2.B.2, section 2.B.

[10] We also assign a 10 percent shift between equal probabilities as suggested by Perozek (2008). The estimation results again change slightly compared to those from the 5 percent shift assumption but they are still significantly different than the results without equal probabilities.

2.2.2 Descriptive Statistics

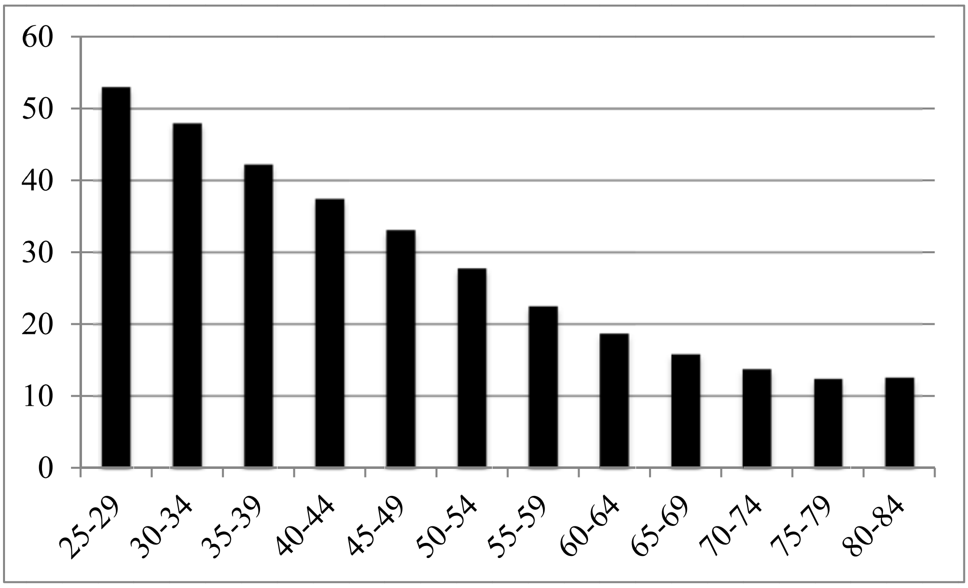
2.2.2.1 Median remaining life duration

Using the respondents' subjective survival probabilities, we compute the subjective median remaining life duration conditional on baseline age for each individual in the sample (equation (2.A.7), section 2.A).

As Figure 2.1 shows, the mean of the median remaining life duration is 53 years for the group aged 25–29 but decreases to about 12 years for the individuals aged 80–84. We observe the date of death of 330 individuals in our sample that die before December 2010.

Figure 2.1

Average subjective remaining life duration across age categories (in years)



A comparison of the subjective and objective (within-sample) remaining life durations across age categories and gender (see Table 2.3) reveals that for females, the subjective values are less than the objective values at all ages, whereas for males, the subjective values are less than the objective values up to age 65 but then exceed their objective counterparts. On average, the difference between subjective and objective remaining life duration is smaller for males than for females. We do note, however, that the remaining life durations based on the HMD life table are always less than their objective counterparts at all ages for both males and females, which may suggest that relatively healthier individuals may be overrepresented in our sample.[11]

Table 2.3: The Mean of Objective and Subjective Remaining Life Duration across Age Categories and Gender (in years)

	Remaining life duration			Remaining life duration		
	Objective*	Subjective		Objective*	Subjective	
Age	(1)	(2)	(2)-(1)	(3)	(4)	(4)-(3)
	Males			Females		
25-29	53.11	52.71	-0.4	59.84	53.27	-6.57
30-34	48.54	47.66	-0.88	55.49	48.31	-7.18
35-39	43.55	42.34	-1.21	50.25	42.13	-8.12
40-44	38.83	37.3	-1.53	45.49	37.61	-7.88
45-49	33.8	32.83	-0.97	40.47	33.49	-6.98
50-54	29.21	27.44	-1.77	35.72	28.13	-7.59
55-59	24.11	22.42	-1.69	30.58	22.55	-8.03
60-64	19.75	18.47	-1.28	25.92	19.05	-6.87
65-69	15.66	15.82	0.16	21.44	15.79	-5.65
70-74	11.73	13.98	2.25	17.25	13.37	-3.88
75-79	8.71	12.21	3.5	13.54	12.66	-0.88
80-84	6.15	11.93	5.78	10.35	13.3	2.95
Sample average	33.36	32.46	-0.9	41.84	34.68	-7.16

Notes: N = 3,059. * The objective remaining life duration is computed based on the estimation of a Gompertz mortality model with only gender and age as covariates.

As shown in Table 2.4, the difference between subjective and objective remaining life duration is minimum for males with low education and for females whose self-reported health status is poor. Overall, the statistics in this section indicate that our "subjective median remaining life duration" measure is informative for within-sample mortality.

[11] For this calculation, we use the 1995 life table available in the Human Mortality Database (HMD). Because cohort life tables are not available for each individual in our sample, we are forced to use period life tables which are likely to underestimate life expectancy compared to cohort life tables when mortality rates decline over time.

Table 2.4: The Mean of the Objective and Subjective Remaining Life Duration across Education, Health Status, and Gender (in years)

	Remaining life duration			Remaining life duration		
Age	Objective (1)	Subjective (2)	(2)-(1)	Objective (3)	Subjective (4)	(4)-(3)
		Males			Females	
Low education	31.13	30.99	-0.14	39.46	32.19	-7.27
Medium education	35.30	33.20	-2.10	43.72	35.36	-8.36
High education	35.73	32.39	-3.34	46.50	36.29	-10.21
In good health*	37.14	33.97	-3.17	46.50	36.26	-10.24
Not in good health*	25.66	24.92	-0.74	35.21	28.55	-6.66

Notes: N = 3,059. *Both education and health are controlled for to obtain the objective remaining life duration.

2.2.2.2 Control variables

Table 2.5 presents the mean, median, and standard deviation of the right-hand side variables and baseline age. Women, with a 45 percent share, are slightly underrepresented in our sample compared to men. The mean age at time of interview is about 47 years, 87.6 percent of the respondents are married, 31.2 percent are smokers, 8 percent drink alcohol,[12] 81.6 percent self-rate their health as good or excellent, and 24.5 percent report a chronic condition such as a long term illness, disorder, or disability. Based on the body weight index (BMI), 33.6 percent of the respondents are overweight, and 6 percent are obese.

The sample consists mostly of medium educated individuals with pre-university education or junior/senior vocational training, and the average annual standardized household income is ƒ44,287 (€20,096). Standardized household income is defined as the sum of the net annual incomes of all household members divided by the equivalence scale provided by Statistics Netherlands (Siermann *et al.*, 2004). Following Delavande and Rohwedder (2011), we create income terciles, which are insensitive to outliers, by dividing the income distribution into three parts. Although not shown in Table 2.5, 28 percent of the respondents are members of the high-income panel, while 72 percent fall into the nationwide representative panel.

[12] The alcohol variable is a dummy variable that takes the value of one if the respondent consumes more than four alcoholic drinks a day and zero otherwise.

Table 2.5: Mean, Median, and Standard Deviation of Variables

Variable	Mean	Median	SD
Gender (0 = male,1 =female)	0.450	0	0.498
Year dummy 1996	0.161	0	0.367
Subjective remaining life duration (in years)	33.460	34.245	12.598
Smoking	0.312	0	0.463
Good health	0.816	1	0.387
Alcohol	0.081	0	0.272
Chronic illness	0.245	0	0.430
Overweight	0.336	0	0.473
Obese	0.060	0	0.237
Low education	0.225	0	0.418
High education	0.400	0	0.490
Standardized income (in Dutch guilders)	44,287	40,757	24,988
Married	0.876	1	0.330
Single	0.100	0	0.300
Widowed	0.020	0	0.154
Age (in years)	47.321	45.833	12.654

Notes: N = 3,059.

2.3 Estimation methodology

Following previous empirical studies on individual mortality, we assume that life duration can be modeled with a (truncated) Gompertz distribution (see, e.g., Gompertz 1825; Olshansky and Carnes 1997; Perozek 2008). One important advantage of this assumption (as demonstrated below) is that it facilitates comparison between the estimated parameters of the subjective and objective mortality models.

2.3.1 Objective Mortality Model

Assuming that respondent i is aged t_0 when he reports his probability of survival to age t, and T is a random variable representing the respondent's age at death, then the survival function, which gives the probability of the respondents' age at death being greater than t, can be written as follows:

$$S(t|\mathbf{x_i}) = \Pr\left(T > t|t_0, \mathbf{x_i}\right) = \exp\left\{-\int_{t_0}^{t} \theta(s|\mathbf{x_i})ds\right\} = \exp\left(-\Lambda_{t_0}(t|\mathbf{x_i})\right), \qquad (2.1)$$

where $\theta(t|\mathbf{x_i})$ is the hazard function of the respondent with characteristics $\mathbf{x_i}$ and $\Lambda_{t_0}(t|\mathbf{x_i})$ is the integrated hazard from age t_0 to age t. Assuming that the random variable T follows a Gompertz distribution, the hazard function can be given by

$$\theta(t|\mathbf{x_i}) = \lambda_i \exp\{\gamma_i t\}, \text{ where } \lambda_i = \lambda_O = \exp\{\mathbf{x_i}\boldsymbol{\beta_O}\} \text{ and } \gamma_i = \gamma_O > 0 \tag{2.2}$$

Each respondent is observed first at age $t_{0,i}$; if the respondent dies at t_i, the contribution of this observation to the likelihood function is the density at that duration:

$$L_i(\boldsymbol{\beta_O}, \gamma_O | \mathbf{x_i}, t_{0,i}, t_i) = f(t_i|\mathbf{x_i}) = S(t_i|\mathbf{x_i})\theta(t_i|\mathbf{x_i}). \tag{2.3}$$

If the respondent is still alive at the end of observation period (where t_i is December 2010), the observation is right-censored, and its contribution to the likelihood is

$$L_i(\boldsymbol{\beta_O}, \gamma_O | \mathbf{x_i}, t_{0,i}, t_i) = S(t_i|\mathbf{x_i}). \tag{2.4}$$

By combining equations (2.3) and (2.4), we can write the log-likelihood function for the whole sample as

$$\log \prod_{i=1}^{N} L_i(\boldsymbol{\beta_O}, \gamma_O | \mathbf{x_i}, t_{0,i}, t_i) = \sum_{i=1}^{N} \left(d_i (\mathbf{x_i}\boldsymbol{\beta_O} + \lambda_O t) - \Lambda_{t_0}(t|\mathbf{x_i}) \right) \tag{2.5}$$

where N is the number of individuals in our sample and d_i is a dummy variable that takes 1 if the respondent has died at time t_i and 0 otherwise. Based on equation (2.5), we obtain the maximum likelihood estimates $\hat{\boldsymbol{\beta}}_{\mathbf{O}}$ and $\hat{\gamma}_O$.

2.3.2 Subjective Mortality Model

For this model, we use the subjective information on mortality to estimate a set of parameters analogous to the parameters of the objective mortality model. As in the objective mortality model, we assume a Gompertz hazard function given by

$\theta(t|\mathbf{x_i}) = \lambda_i \exp\{\gamma_i t\}$, where $\lambda_i = \lambda_S = \exp\{\mathbf{x_i}\boldsymbol{\beta}_S\}$ and $\gamma_i = \gamma_S > 0$

We can then estimate the following system of linear equations:

$$\gamma_i^* = \gamma_S + \varepsilon_{1i} \tag{2.6}$$

$$\ln\left(\lambda_i^*\right) = \mathbf{x}_i^{'}\boldsymbol{\beta}_S + \varepsilon_{2i} \tag{2.7}$$

where γ_i^* and λ_i^* are the estimated parameters of the individual survival functions (as shown in section 2.A), and ε_{1i} and ε_{2i} stand for the error terms, which are allowed to be correlated with each other. We obtain the $\hat{\boldsymbol{\beta}}_S$ and $\hat{\gamma}_S$ estimates using Seemingly Unrelated Regressions estimation (Zellner, 1962).

2.4 Empirical Results

2.4.1 The predictive power of subjective survival for actual mortality

We first estimate an objective mortality risk model as outlined in Section 2.3 and then stepwise, include a set of covariates (socioeconomic variables and health indicators) in addition to the subjective (median) remaining life duration.[13] Based on a likelihood ratio test, we do not reject pooling the male and female samples at a 5 percent level of significance (for all models) and, therefore, include a control variable for gender instead of reporting separate results for men and women. The estimation results are given in Table 2.6.

The first model estimated explains mortality risk only as a function of year dummy, age, and subjective remaining life duration. The coefficient of subjective remaining life duration is negative and statistically significant, suggesting, in line with the previous studies, that those who expected to live longer at the baseline year experienced a lower mortality risk than those whose life expectation was shorter. The second model, which includes additional controls for gender and education, shows that the coefficient estimate of subjective remaining life duration remains significant but at a 5 percent level of significance. This model also suggests that, as might be expected, women have a lower mortality risk than men. The *p*-value of the Wald test for education also indicates that the coefficients of high and low education are jointly significant but only at a 10 percent level of significance. In the third model, to which we add standardized household income terciles and marital status as control variables, the coefficient of the subjective remaining life duration is still significant at a 5 percent level of significance. Respondent's income level and marital status have no significant effect on actual mortality.

[13] When we replace the median remaining life duration with its natural logarithm, the results are rather similar; its coefficient is significant at the 5 percent significance level in all models shown in Table 2.6 except model (4).

Table 2.6: Estimation Results for the Objective Mortality Model

Covariates	(1)	(2)	(3)	(4)
Subjective remaining life duration	-0.002***	-0.002**	-0.002**	-0.0004
	(0.001)	(0.001)	(0.001)	(0.0008)
Year dummy 1996	0.041	0.034	0.035	0.063
	(0.187)	(0.188)	(0.188)	(0.189)
Female		-0.777***	-0.773***	-0.778***
		(0.127)	(0.130)	(0.133)
Low education		0.100	0.109	0.163
		(0.140)	(0.141)	(0.141)
High education		-0.207	-0.130	-0.040
		(0.130)	(0.137)	(0.139)
Lowest standardized income tercile			0.116	0.038
			(0.133)	(0.135)
Highest standardized income tercile			-0.107	-0.043
			(0.142)	(0.143)
Single			0.221	0.097
			(0.186)	(0.188)
Widowed			0.136	0.103
			(0.206)	(0.207)
Smoking				0.728***
				(0.124)
Good health				-0.443***
				(0.138)
Alcohol				0.297*
				(0.173)
Overweight				-0.089
				(0.120)
Obese				0.465**
				(0.191)
Chronic illness				0.260*
				(0.133)
Constant	-10.531***	-10.396***	-10.415***	-11.471***
	(0.520)	(0.523)	(0.527)	(0.561)
Age	0.008***	0.008***	0.008***	0.009***
	(0.001)	(0.001)	(0.001)	(0.001)
Log likelihood	-351.264	-330.569	-328.477	-292.933
p-value Wald test: education		0.092	0.302	0.377
p-value Wald test: education and income			0.141	0.605
p-value Wald test: education, income, marital status			0.169	0.787
p-value Wald test: overweight and obese				0.019

Notes: N = 3,059; no. of failures = 330; standard errors given in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

When health indicators are added to the set of covariates, in contrast, the coefficient of subjective remaining life duration becomes smaller and is no longer statistically significant. In other words, the predictive power of SSPs in explaining mortality disappears once health indicators are controlled for. This finding suggests that SSPs' predictive power for actual mortality, being largely determined by the observed current health situation, is rather limited and contains little additional information on future health expectations. Among the health indicators, smoking, drinking, being in good health, obesity, and having chronic illnesses are statistically significant determinants of mortality risk, with the coefficients of obesity and overweight being jointly significant. The coefficient of year dummy for 1996 is insignificant, but as is to be expected, in all models, mortality risk increases significantly with age.

We then use the coefficient estimates of the third and the fourth models in Table 2.6 to predict the median remaining life duration conditional on baseline age (see equation (2.A.8), section 2.A.1). The first panel in Table 2.7 shows the response of predicted median remaining life duration based on observed mortality to a change in the subjective median remaining life duration of five years.

Table 2.7: Predicted Median Remaining Life Duration based on Estimates from the Objective Mortality Model (in years)

	Baseline age	Subjective remaining life duration		Predicted objective remaining life duration		Change in predicted remaining life duration	
		(a)	(b)	(a)	(b)	Point estimate (b)-(a)	*p*-value*
Panel A: Change in male subjective remaining life duration							
With health controls †	45	34	39	38.872	39.092	0.220	0.605
No health controls ‡	45	34	39	40.784	41.793	1.009	0.054
Panel B: Gender differences without control variables							
				Male (a)	Female (b)	Point estimate (b)-(a)	*p*-value*
	45	-	-	37.676	44.085	6.409	0.000

Notes: N = 3,059. †The reference category is a married man living in a medium income household, who reported his SSPs in 1995,with no chronic illnesses, non-smoker, non-drinker, of normal weight, medium-level education, but not in good health. ‡The reference category is a married, medium educated man living in middle income household, who reported his SSP in 1995.**p*-values are the result of a two-tailed *t*-test.

In the model controlling for socioeconomic variables and health indicators, for 45-year-old men reported their SSPs in 1995, a five-year change in the subjective median remaining life duration (from 34 to 39 years) results in a change in the predicted median remaining life duration of only 0.22 years.[14] That this difference is statistically insignificant is not surprising given that subjective remaining life duration can no longer predict mortality risk once health indicators are controlled for. When health indicators are excluded, the correlation becomes stronger: for 45-year-old men reported their SSPs in 1995, five years of additional subjective remaining life duration corresponds to about one year longer life duration, an increase that is statistically significant.

The second panel in Table 2.7 reports the male-female difference in predicted remaining median life duration implied by the objective mortality model. It shows a 6.4 years higher predicted median for 45-year-old women than for men of the same age, a significantly positive difference. Using the 1995 HMD life tables, we find that the male-female difference in median life expectancy at age 45 is 6.05 years, only slightly smaller than our model predicts. This proximity suggests some confidence in our model and the estimated age and gender effects.[15]

2.4.2 Objective and Subjective Mortality Risk Models

This section reports the estimation results for the subjective and objective mortality risk models when we include the same socioeconomic variables and health indicators in each model. If respondents in the sample are able to predict their remaining lifetime correctly, we expect that the signs and magnitudes of the estimates obtained from the objective mortality model will coincide with those obtained from the subjective mortality.

The first two models reported in Table 2.8 explain subjective and objective mortality risk as a function of year dummy, age effects, and socioeconomic variables. In both models, the coefficient estimate of age has the same sign and is statistically significant although the age gradient is steeper in subjective than in actual mortality model. The coefficient of female in the subjective model is insignificant although the objective model predicts that women have lower mortality risks than men, on average.

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[14] Predictions are virtually the same for 45-year-old women, which can be expected from the use of a proportional hazard specification.

[15] As already pointed out, if mortality rates decline over time, the period life tables used are likely to underestimate life expectancy compared to cohort life tables.

Table 2.8: Estimation Results for the Objective and Subjective Mortality Risk Models

	Subjective	Objective	Subjective	Objective	Subjective	Objective
Covariates	(1)	(2)	(3)	(4)	(5)	(6)
Year dummy 1996	0.026	0.391	0.001	0.086	0.024	0.065
	(0.056)	(0.188)	(0.053)	(0.188)	(0.059)	(0.188)
Female	0.005	-0.788***	0.001	-0.735***	0.012	-0.782***
	(0.042)	(0.129)	(0.040)	(0.127)	(0.045)	(0.133)
Low education	0.007	0.111			-0.010	0.164
	(0.054)	(0.141)			(0.057)	(0.141)
High education	0.027	-0.142			0.060	-0.041
	(0.048)	(0.137)			(0.052)	(0.139)
Lowest standardized income tercile	-0.018 (0.050)	0.098 (0.133)			-0.021 (0.053)	0.034 (0.135)
Highest standardized income tercile	0.094* (0.050)	-0.119 (0.142)			0.118** (0.053)	-0.042 (0.143)
Single	-0.024	0.236			-0.065	0.098
	(0.068)	(0.186)			(0.072)	(0.188)
Widowed	-0.239*	0.142			-0.276*	0.106
	(0.132)	(0.206)			(0.141)	(0.206)
Smoking			0.162***	0.741***	0.179***	0.730***
			(0.043)	(0.123)	(0.047)	(0.124)
Good health			-0.220***	-0.465***	-0.239***	-0.455***
			(0.058)	(0.135)	(0.064)	(0.136)
Alcohol			0.130*	0.305*	0.124	0.302*
			(0.074)	(0.171)	(0.081)	(0.173)
Overweight			-0.016	-0.074	-0.007	-0.089
			(0.043)	(0.119)	(0.047)	(0.120)
Obese			0.175**	0.493***	0.122**	0.470**
			(0.084)	(0.189)	(0.093)	(0.191)
Chronic illness			0.073	0.281**	0.082	0.266**
			(0.053)	(0.131)	(0.057)	(0.132)
Constant	-14.543***	-11.409***	-14.411***	-11.730***	-14.456***	-11.711***
	(0.173)	(0.272)	(0.178)	(0.308)	(0.186)	(0.335)
Age	0.014***	0.009***	0.014***	0.010***	0.014***	0.010***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
p-value Wald test: income	0.069	0.356	-	-	0.027	0.886
p-value Wald test: education, income, and marital status	0.104	0.142	-	-	0.010	0.789
p-value Wald test: BMI			0.086	0.014	0.059	0.017

Notes: N = 3,059; no. of failures = 330; standard errors given in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

We also run a Wald test to see if the coefficient on female in the subjective model is equal to that in the objective model and we strongly reject that the coefficient estimates are equal to the each other (not reported in Table 2.8). This suggests that males and females have similar beliefs about survival probabilities and females do not think that they will live longer than males, on average. The coefficients of income terciles in the subjective model have opposite signs meaning that, taking household size and composition into account, those living in a high income household have significantly higher mortality risks than those living in a middle income household. The estimated coefficient on high education indicates that more educated have higher mortality risks than medium educated although it is statistically insignificant. This finding is at odds with Delavande and Rohwedder (2011) which finds that college graduates report higher survival chances than individuals with lower education.

According to Table 2.8, contrary to objective model's predictions, widowed individuals have lower mortality risks than married individuals. The third and the fourth models show the estimated coefficients on year dummy, gender, age, and health indicators. Among the health indicators, smoking, drinking, being in good health, and obesity explain subjective mortality risk, yet their associations with subjective survival chances are less strong than with objective survival. The Wald test (not reported in Table 2.8) for the equality of coefficient estimates on health indicators in subjective and objective mortality models suggests that the estimated coefficient on smoking in subjective model is statistically different than that in objective model whereas we cannot reject the null hypothesis for the other health indicators. A smaller coefficient on smoking in the subjective model than in the objective model implies that individuals underestimate the health risks of smoking.

In the last two models in Table 2.8, which control for both socioeconomic variables and health indicators, the coefficients of age, smoking, good health, and obese have the same sign and are all significant. A Wald test (not reported in Table 2.8) for the equality of the coefficient estimates in these two models reveals that coefficients on female, smoking, and age in the subjective model are statistically different than those in the objective model whereas we cannot find significant differences for the rest of the variables. These results altogether suggest that women significantly underestimate their survival chances compared to their observed survival chances within the sample. Even after controlling for socioeconomic variables, we also find that individuals underestimate the risks from smoking when they answer survival probability questions. This finding is in line with the study by Hurd (2009) which shows that, in the U.S., smokers overestimate their survival chances relative to their actual survival rates within the sample. In this richer model specification, the coefficients on highest income tercile and widowed still have unexpected signs and they are statistically significant at 5 and 10 percent, respectively. Moreover, the *p*-value of the Wald test indicates that the coefficients of income, education, and marital status are jointly significant at 5 percent in the subjective model.

Next we examine whether respondents over- or underestimate their median remaining lifetime by using the coefficient estimates in columns (5) and (6) of Table 2.8 (see equation (2.A.9) and (2.A.10), section 2.A.2) to estimate the predicted median remaining life duration implied by the objective and subjective mortality models.

Table 2.9: Objective versus Subjective Predicted Life Duration (in years)

Characteristics	Objective predicted remaining life duration (1)	Subjective predicted remaining life duration (2)	(2)-(1)
Predictions using SES and HEALTH variables			
Man (reference) †	38.113	36.869	-1.244
Woman	44.829	36.801	-8.028
Man living in a low income household	37.826	36.990	-0.836
Man living in a middle income household	38.113	36.869	-1.244
Man living in a high income household	38.474	36.190	-2.284
Low educated man	36.713	36.925	0.212
Medium educated man	38.113	36.869	-1.244
High educated man	38.467	36.523	-1.944
Smoking man	31.907	35.838	3.931
Man in good health	42.013	38.249	-3.765
Man drinking alcohol	35.538	36.154	0.617
Man with chronic illnesses	35.839	36.398	0.559
Obese man	34.112	35.636	1.524

Notes: †The reference is a 45-year old married man living in a middle income household who reported his SSPs in 1995, with no chronic illnesses, non-smoker, non-drinker, of normal weight and medium education, but not in good health.

According to the results in Table 2.9, although both male and female 45-year-olds underestimate their remaining life duration, women tend to do so much more than men. The underestimation for a reference man and woman is 1.2 and 8 years, respectively. Similarly, Teppa (2012) finds that both Dutch men and women have lower SSPs relative to actuarial survival probabilities, on average, while women underestimate their survival chances more than men. Moreover, Perozek (2008) noted that, based on the fitted survival functions, women are pessimistic about their survival chances relative to men in the United States.

Table 2.9 also shows that, among 45-year-old men, those living in a low (high) income household underestimate their remaining lifetime slightly less (more) than those living in a middle income household, and highly educated men underestimate their remaining lifetime more than medium educated men. Men with a low education level also seem to predict their remaining lifetime better than those with a medium education level, although Table 2.8 shows that corresponding parameter estimates are not significantly different from zero, hence these differences should be interpreted with some caution.

According to Table 2.9, both 45-year-old healthy males and unhealthy (reference) males of the same age underestimate their remaining lifetime, yet the prediction error is larger in the case of healthy males. This finding is consistent with the results in Table 2.8—specifically, a higher (negative) estimated coefficient in the subjective than in the objective model—healthy tend to overestimate their mortality risk more than unhealthy individuals. Table 2.8 also shows that estimated coefficient on smoking is lower in the subjective than in the objective model, meaning that smokers underestimate their mortality risk. As a result, they significantly overestimate their remaining lifetime compared to non-smokers, as it is shown in Table 2.9. We also find a small difference between subjective and objective remaining lifetimes for obese men, men with chronic illnesses and men drinking alcohol.

2.5 Conclusions

Our research of whether individuals' subjective survival probabilities (SSPs) convey useful information on their actual (objective) mortality produces several important findings. In our sample, drawn from the 1995/96 DNB Household Survey and supplemented with information on actual mortality from the causes of death registry up to and including 2010, Dutch life expectancy as measured by SSPs does indeed predict actual mortality in models that control for income and education level. This predictive power disappears, however, when we control for strong health indicators like self-rated health and smoking behavior. This finding suggests that SSPs' predictive power may be limited by their dependence on perceived current health status and they offer little additional information on expected future health events. Yet, SSPs do correlate with the determinants of objective (actual) mortality. Dutch men and women underestimate, on average, their remaining life duration by about 1 and 8 years, respectively. We further show that individuals underestimate the risks from smoking.

Underestimation of survival probabilities has implications for individuals' long term decisions, such as those on retirement and savings, whose outcomes may be suboptimal. For example, those who think that they will not live until old age may not save enough to finance consumption at retirement. Therefore, our research implies important directions for future research. In particular, we believe that more investigation is needed into why Dutch men and, especially, women underestimate their life expectancies. Could it be, for instance, that the concept of SSPs is not clear to many respondents or that some respondents lack basic knowledge on actuarial life duration and behavioral health risks? Such questions need to be answered before we can confidently employ SSPs in economic models (e.g., life cycle models of saving, consumption, and retirement) under the assumption that they convey useful information on individuals' beliefs about mortality risks.

2.A Derivation of the Median Remaining Life Duration

For each individual in our sample, we observe two values of the survival function, $SSP_{1,i}$ and $SSP_{2,i}$, at two different target ages $t_{1,i}$ and $t_{2,i}$ where $t_{1,i} < t_{2,i}$. $t_{0,i}$ is the baseline age; that is, the age at which the respondent reports the SSPs:[16]

$$S_{1,i}(t_{0,i}, t_{1,i}) = \exp\left\{ -\int_{t_{0,i}}^{t_{1,i}} \theta(s) ds \right\} = SSP_{1,i} \qquad (2.A.1)$$

[16] In the mortality hazard model, we measure time in months. Because the initial age in our sample is 25, we are interested in survival from $t_{0,i} - 25$ to $t_i - 25$ where t_i is respondent age at death (if deceased) or respondent age at the end of the DO survey (if still alive at the end of the observation period). Target ages are changed accordingly. For example, instead of $t_{1,i}$=75, we use $t_{1,i}$=75*12-25*12=600. Similarly, $t_{0,i}$=$t_{0,i}$ in months-300. For the sample (50+), instead of $t_{1,i}$=75 we use $t_{1,i}$=75*12-50*12=300, and $t_{0,i}$=$t_{0,i}$ in months-600.

$$S_{2,i}(t_{0,i}, t_{2,i}) = \exp\left\{-\int_{t_{0,i}}^{t_{2,i}} \theta(s)ds\right\} = SSP_{2,i} \tag{2.A.2}$$

with $(t_{1,i}, t_{2,i}) \in \{(75,80),(80,85),(85,90),(90,95),(95,100)\}$ and $(SSP_{1,i}, SSP_{2,i}) \in \{(P75, P80),(P80, P85),(P85, P90),(P90, P95),(P95, P100)\}$, respectively. $P75$ represents the subjective survival probability (SSP) to age 75, $P80$ that to age 80, and so on.

The Gompertz hazard function is given by

$\theta(t) = \lambda_i \exp\{\gamma_i t\}$, $\gamma_i > 0$ for each i, meaning that hazard increases over time (positive duration dependence).

After substituting the hazard rate into equations (2.A.1) and (2.A.2), we evaluate the integral to find

$$S_{1,i}\left(\gamma_i, \lambda_i \middle| t_{0,i}, t_{1,i}\right) = \exp\left\{\frac{\lambda_i}{\gamma_i}\left(\exp\{\gamma_i t_{0,i}\} - \exp\{\gamma_i t_{1,i}\}\right)\right\} = SSP_{1,i} \tag{2.A.3}$$

$$S_{2,i}\left(\gamma_i, \lambda_i \middle| t_{0,i}, t_{2,i}\right) = \exp\left\{\frac{\lambda_i}{\gamma_i}\left(\exp\{\gamma_i t_{0,i}\} - \exp\{\gamma_i t_{2,i}\}\right)\right\} = SSP_{2,i} \tag{2.A.4}$$

Following Perozek (2008), we take logarithms of the survival functions (equation (2.A.5)) and estimate the parameters γ_i and λ_i for each individual using nonlinear least squares (NLLS). This procedure requires that we replace survival probabilities of 0 and 1 with slightly different numbers, namely, 0.01 and 0.99, respectively.

$$\ln\left(SSP_{j,i}\right) = \ln\left(S_{j,i}\left(\gamma_i, \lambda_i \middle| t_{0,i}, t_{j,i}\right)\right) + \varepsilon_{j,i} \qquad j \in \{1,2\} \tag{2.A.5}$$

where $\varepsilon_{j,i}$ is the error term, which is assumed to be independent, identically distributed (i.i.d.), and homoscedastic, and have a zero mean.

The NLLS estimates of γ_i^* and λ_i^* are obtained by minimizing the following expression:

$$\min_{\gamma_i, \lambda_i} \sum_j \left(\ln\left(SSP_{j,i}\right) - \ln\left(S_{j,i}\left(\gamma_i, \lambda_i \middle| t_{0,i}, t_{j,i}\right)\right)\right)^2$$

with $S_{j,i}\left(\gamma_i,\lambda_i\middle|t_{0,i},t_{j,i}\right)=\exp\left\{\frac{\lambda_i}{\gamma_i}\left(\exp\{\gamma_i t_{0,i}\}-\exp\{\gamma_i t_{j,i}\}\right)\right\}$

Next, we calculate the median remaining life duration conditional on baseline age for each individual (RL_i^S) based on the following formula:[17]

$$S(RL_i^S|t_{0,i})=\exp\left\{-\int_0^{RL_i^S}\theta(s'+t_{0,i})ds'\right\}=0.5 \qquad (2.A.6)$$

The Gompertz hazard function is $\theta(s'+t_{0,i})=\lambda_i\exp\{\gamma_i(s'+t_{0,i})\}$, $\gamma_i>0$ for each i. Evaluating the integral in equation (2.A.6) and taking the natural logarithm of both sides yields

$$-\ln(0.5)=\frac{\lambda_i}{\gamma_i}\left(\exp\{\gamma_i(t_{0,i}+RL_i^S)\}-\exp\{\gamma_i t_{0,i}\}\right)$$

$$RL_i^S=\frac{1}{\gamma_i}\ln\left(\frac{\gamma_i\ln(2)}{\lambda_i\exp(\gamma_i t_{0,i})}+1\right) \qquad (2.A.7)$$

In equation (2.A.7), we replace γ_i and λ_i with their estimates γ_i^* and λ_i^*, respectively. Because the variable, RL_i^S , is created using individuals' subjective survival probabilities, it represents the subjective median remaining life duration conditional on baseline age for each individual.

2.A.1 Predictions Using the Estimates of the Objective Mortality Model (Table 2.7)

The assumption maintained in the objective mortality model is that there is a Gompertz hazard function given by

$\theta(t|\mathbf{x_i})=\lambda_i\exp\{\gamma_i t\}$, where $\lambda_i=\lambda_O=\exp\{\mathbf{x_i}\boldsymbol{\beta_O}\}$ and $\gamma_i=\gamma_O>0$

[17] We calculate the median remaining life duration conditional on baseline age because respondents report their SSPs knowing that they have survived up to their current age.

By combining this assumption with equation (2.A.7) and replacing λ_O and γ_O with the estimates of the objective mortality model given in Table 2.6, we can derive the following equation:

$$\hat{RL}^O = \frac{1}{\hat{\gamma}_O} \ln\left(\frac{\hat{\gamma}_O \ln(2)}{\exp\left\{ \bar{\mathbf{x}}_\mathbf{i} \hat{\boldsymbol{\beta}}_\mathbf{O} + \hat{\gamma}_O \bar{t}_{0,i} \right\}} + 1 \right) \tag{2.A.8}$$

where $\hat{RL}^O$ is the objective predicted remaining life duration and $\bar{t}_{0,i}$ is the baseline age, which is equal to 45. The vector $\bar{\mathbf{x}}_\mathbf{i}$ contains the mean value of the logarithm of household income and fixed values of the remaining variables shown in Table 2.7. For example, in the first row of Table 2.7, all of the dummy variables in the objective mortality model are equal to zero, subjective remaining life duration takes a value of 410 or 470, and birth year is equal to 1950.

2.A.2 Comparison of the Objective and the Subjective Predicted Life Durations (Table 2.9)

The common assumption in the objective and subjective mortality models is that life duration can be modeled using a Gompertz distribution. Under this assumption, the hazard function can be written as

$$\theta(t|\mathbf{x}_\mathbf{i}) = \lambda_i \exp\{\gamma_i t\}$$

where $\lambda_i = \lambda_O = \exp\{\mathbf{x}_\mathbf{i}\boldsymbol{\beta}_\mathbf{O}\}$, $\gamma_i = \gamma_O > 0$ in the objective mortality model, and $\lambda_i = \lambda_S = \exp\{\mathbf{x}_\mathbf{i}\boldsymbol{\beta}_S\}$, $\gamma_i = \gamma_S > 0$ in the subjective mortality model. In equation (2.A.7), we replace λ_O, γ_O, λ_S, and γ_S with their estimates, $\hat{\lambda}_O$, $\hat{\gamma}_O$, $\hat{\lambda}_S$, and $\hat{\gamma}_S$, respectively:

$$\hat{RL}^O = \frac{1}{\hat{\gamma}_O} \ln\left(\frac{\hat{\gamma}_O \ln(2)}{\exp\left\{ \bar{\mathbf{x}}_\mathbf{i} \hat{\boldsymbol{\beta}}_\mathbf{O} + \hat{\gamma}_O \bar{t}_{0,i} \right\}} + 1 \right) \tag{2.A.9}$$

$$\hat{RL}^{S} = \frac{1}{\hat{\gamma}_S}\ln\left(\frac{\hat{\gamma}_S \ln(2)}{\exp\left\{\bar{\mathbf{x}}_{\mathbf{i}}\hat{\boldsymbol{\beta}}_{\mathbf{S}} + \hat{\gamma}_S \bar{t}_{0,i}\right\}} + 1\right) \tag{2.A.10}$$

where $\hat{RL}^{O}$ and $\hat{RL}^{S}$ denote objective and subjective predicted remaining life durations, respectively, and $\bar{t}_{0,i}$ is the baseline age, which is equal to 45. The vector $\bar{\mathbf{x}}_{\mathbf{i}}$ contains the mean value of the logarithm of household income and fixed values of the remaining variables shown in Table 2.9. For example, in the first row of Table 2.9, all of the dummy variables in both mortality models are equal to zero and birth year is equal to 1950.

2.B Tabulation of survival probabilities and variable definitions

Table 2.B.1: Tabulation of Survival Probabilities (%)

	0.01	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9	0.99
P75	1.67	0.58	1.64	1.73	2.95	27.44	11.56	16.06	22.6	6.72	7.03
P80	4.27	2.14	5.41	8.63	10.74	30.09	16.7	13.39	6.72	1.68	X
P85	6.32	3.57	8.24	13.74	11.81	31.87	10.16	6.59	4.67	X	X
P90	19.23	11.54	13.94	10.58	9.13	25.96	X	X	X	X	X

Notes: N = 3,059. X means that the number in this cell cannot be released by the CBS since the number of units underlying this cell is less than 10. We do not report survival probabilities to age 95 or age 100 because the number of observations is so small. For the reasons given in 2.A, we replace survival probability answers 0 and 1 with 0.01 and 0.99, respectively.

Table 2.B.2: Variable Definitions

Variable	Description	Baseline
RL_i^S	Subjective median remaining life duration conditional on baseline age	---
Female	Respondent is female	Respondent is male
Low education	Respondent has primary/low level education or vocational training through the apprentice system	Respondent has pre-university education or junior/senior vocational training
High education	Respondent has a university degree or a vocational college degree.	Respondent has pre-university education or junior/senior vocational training
Standardized household income (in Dutch guilders)	The sum of the net annual incomes of all household members after deduction of taxes but before making payments such as rent, mortgages, etc. divided by the equivalence scale provided by Statistics Netherlands (Siermann *et al*., 2004)	---
Lowest standardized income tercile	Respondent's standardized household income is lower than and equal to the 33th percentile of the standardized household income series	Respondent's standardized household income is between the 33th and 67th percentiles of standardized household income series
Highest standardized income tercile	Respondent's standardized household income is higher than and equal to the 67th percentile of the standardized household income series	Respondent's standardized household income is between the 33th and 67th percentiles of standardized household income series
Good health	Respondent's self-reported health is excellent/good	Respondent's self-reported health is fair/not so good/poor
Smoking	Respondent is smoker	Respondent is non-smoker
Alcohol	Respondent consumes more than 4 alcoholic drinks a day	Respondent does not consume more than 4 alcoholic drinks a day
Chronic illness	Respondent suffers from long- term illness, disorder, disability, or the consequences of an accident	Respondent does not suffer from long-term illness, disorder, disability, or the consequences of an accident
Overweight	25≤ Respondent's body mass index (BMI)< 30	Respondent's BMI< 25
Obese	Respondent's BMI≥ 30	Respondent's BMI< 25
Year dummy 1996	Respondent reported his/her SSP in 1996	Respondent reported his/her SSP in 1995
Single	Respondent is single	Respondent is married
Widowed	Respondent is widowed	Respondent is married
Age	Respondent's age in months at the time of interview	---

2.C Estimation results without excluding equal probabilities

Table 2.C.1: Estimation Results for the Objective Mortality Model

Covariates	(1)	(2)	(3)	(4)
Subjective remaining life duration	-0.002***	-0.002***	-0.002***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Year dummy 1996	0.046	0.041	0.043	0.101
	(0.149)	(0.149)	(0.149)	(0.151)
Female		-0.782***	-0.784***	-0.766***
		(0.105)	(0.107)	(0.109)
Low education		0.065	0.069	0.065
		(0.115)	(0.116)	(0.117)
High education		-0.281**	-0.234**	-0.152
		(0.111)	(0.118)	(0.119)
Lowest standardized income tercile			0.174	0.104
			(0.118)	(0.119)
Highest standardized income tercile			0.036	0.050
			(0.119)	(0.119)
Single			0.249	0.107
			(0.155)	(0.157)
Widowed			0.107	0.052
			(0.177)	(0.177)
Smoking				0.662***
				(0.104)
Good health				-0.374***
				(0.118)
Alcohol				0.283*
				(0.146)
Overweight				-0.004
				(0.100)
Obese				0.428**
				(0.167)
Chronic illness				0.239**
				(0.112)
Constant	-10.048***	-9.789***	-9.863***	-10.656***
	(0.362)	(0.363)	(0.369)	(0.389)
Age	0.007***	0.008***	0.007***	0.008***
	(0.000)	(0.000)	(0.000)	(0.000)
Log likelihood	-538.612	-507.866	-505.239	-464.522
p-value Wald test: education		0.009	0.050	0.244
p-value Wald test: education and income			0.020	0.336
p-value Wald test: education, income, marital status			0.021	0.527
p-value Wald test: overweight and obese				0.029

Notes: Estimation results are based on the sample aged 25+ with respondents reporting equal survival probabilities included. We assume a 5 percent shift between equal survival probabilities. N = 4,434; no. of failures = 463; standard errors given in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Table 2.C.2: Estimation Results for the Objective and the Subjective Mortality Risk Models

	Subjective	Objective	Subjective	Objective	Subjective	Objective
Covariates	(1)	(2)	(3)	(4)	(5)	(6)
Year dummy 1996	0.015	0.063	-0.004	0.131	0.016	0.114
	(0.048)	(0.149)	(0.042)	(0.150)	(0.048)	(0.151)
Female	-0.072*	-0.798***	-0.087***	-0.737***	-0.060	-0.780***
	(0.037)	(0.107)	(0.032)	(0.105)	(0.038)	(0.109)
Low education	0.019	0.058			-0.005	0.054
	(0.047)	(0.116)			(0.047)	(0.116)
High education	0.115***	-0.242**			0.147***	-0.153
	(0.043)	(0.118)			(0.043)	(0.119)
Lowest standardized	-0.054	0.144			-0.059	0.079
income tercile	(0.045)	(0.118)			(0.045)	(0.119)
Highest standardized	0.023	0.024			0.038	0.050
income tercile	(0.045)	(0.119)			(0.044)	(0.119)
Single	0.012	0.280*			-0.029	0.112
	(0.061)	(0.155)			(0.061)	(0.157)
Widowed	-0.061	0.087			-0.118	0.051
	(0.118)	(0.177)			(0.118)	(0.177)
Smoking			0.098***	0.689***	0.121***	0.663***
			(0.035)	(0.102)	(0.039)	(0.103)
Good health			-0.397***	-0.450***	-0.411***	-0.438***
			(0.048)	(0.116)	(0.054)	(0.116)
Alcohol			0.162***	0.316**	0.152**	0.321**
			(0.060)	(0.144)	(0.068)	(0.145)
Overweight			0.005	0.018	0.022	0.001
			(0.034)	(0.099)	(0.039)	(0.100)
Obese			0.125*	0.471***	0.171**	0.444***
			(0.068)	(0.166)	(0.078)	(0.167)
Chronic illness			0.063	0.278**	0.072	0.262**
			(0.042)	(0.111)	(0.048)	(0.112)
Constant	-12.834***	-11.227***	-12.525***	-11.495***	-12.589***	-11.451***
	(0.133)	(0.219)	(0.138)	(0.254)	(0.146)	(0.271)
Age	0.011***	0.009***	0.011***	0.009***	0.011***	0.009***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
p-value Wald test: income	0.229	0.431	-	-	0.106	0.793
p-value Wald test: education, income, and marital status	0.019	0.023	-	-	0.000	0.618
p-value Wald test: BMI			0.186	0.015	0.093	0.023

Notes: Estimation results are based on the sample aged 25+ with respondents reporting equal survival probabilities included. We assume a 5 percent shift between equal survival probabilities. N = 4,434; no. of failures = 463; standard errors given in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

2.D Estimation results with individuals aged 50 and older

Table 2.D.1: Estimation Results for the Objective Mortality Model

Covariates	(1)	(2)	(3)	(4)
Subjective remaining life duration	-0.002**	-0.002**	-0.002*	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
Year dummy 1996	0.062	0.065	0.048	0.094
	(0.214)	(0.215)	(0.215)	(0.217)
Female		-0.837***	-0.830***	-0.832***
		(0.141)	(0.144)	(0.148)
Low education		0.168	0.173	0.234
		(0.153)	(0.154)	(0.154)
High education		-0.124	-0.016	0.072
		(0.142)	(0.151)	(0.154)
Lowest standardized income tercile			-0.203	0.100
			(0.171)	(0.144)
Highest standardized income tercile			0.143	-0.081
			(0.141)	(0.173)
Single			0.064	-0.029
			(0.216)	(0.220)
Widowed			0.096	0.081
			(0.210)	(0.211)
Smoking				0.609***
				(0.142)
Good health				-0.414***
				(0.149)
Alcohol				0.253
				(0.200)
Overweight				-0.021
				(0.131)
Obese				0.463**
				(0.211)
Chronic illness				0.271*
				(0.143)
Constant	-8.371***	-8.238***	-8.262***	-8.915***
	(0.371)	(0.376)	(0.386)	(0.426)
Age	0.009***	0.009***	0.009***	0.010***
	(0.001)	(0.001)	(0.001)	(0.001)
Log likelihood	-354.957	-335.432	-333.191	-310.639
p-value Wald test: education		0.188	0.446	0.313
p-value Wald test: education and income			0.121	0.434
p-value Wald test: education, income, marital status			0.263	0.687
p-value Wald test: overweight and obese				0.068

Notes: The estimation results are based on the sample aged 50+ with respondents reporting equal survival probabilities excluded. $N = 1{,}142$; no. of failures = 277; standard errors given in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 2.D.2: Estimation Results for the Objective and the Subjective Mortality Risk Models

	Subjective	Objective	Subjective	Objective	Subjective	Objective
Covariates	(1)	(2)	(3)	(4)	(5)	(6)
Year dummy 1996	0.011	0.064	0.006	0.143	0.020	0.102
	(0.115)	(0.215)	(0.118)	(0.214)	(0.123)	(0.216)
Female	-0.022	-0.843***	-0.037	-0.802***	-0.026	-0.838***
	(0.075)	(0.144)	(0.076)	(0.140)	(0.082)	(0.147)
Low education	0.025	0.172			0.015	0.234
	(0.092)	(0.153)			(0.099)	(0.154)
High education	0.022	-0.022			0.046	0.072
	(0.088)	(0.151)			(0.095)	(0.154)
Lowest standardized	-0.127	0.138			-0.144	0.098
income tercile	(0.089)	(0.142)			(0.095)	(0.144)
Highest	0.051	-0.229			0.117	-0.085
standardized income tercile	(0.088)	(0.171)			(0.095)	(0.173)
Single	0.101	0.082			0.048	-0.024
	(0.129)	(0.216)			(0.138)	(0.220)
Widowed	-0.171	0.107			-0.152	0.088
	(0.152)	(0.210)			(0.163)	(0.211)
Smoking			0.125	0.618***	0.139	0.611***
			(0.088)	(0.140)	(0.092)	(0.142)
Good health			-0.258***	-0.442***	-0.281***	-0.435***
			(0.096)	(0.145)	(0.101)	(0.147)
Alcohol			0.223*	0.249	0.211	0.261
			(0.132)	(0.197)	(0.138)	(0.199)
Overweight			-0.064	-0.023	-0.055	-0.027
			(0.077)	(0.130)	(0.081)	(0.131)
Obese			0.136	0.482**	0.183	0.466**
			(0.145)	(0.209)	(0.153)	(0.211)
Chronic illness			0.127	0.295**	0.156*	0.277*
			(0.088)	(0.140)	(0.092)	(0.143)
Constant	-10.274***	-8.859***	-10.170***	-9.082***	-10.187***	-9.133***
	(0.178)	(0.242)	(0.193)	(0.277)	(0.210)	(0.312)
Age	0.015***	0.010***	0.014***	0.010***	0.015***	0.010***
	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
p-value Wald test: income	0.140	0.109	-	-	0.035	0.576
p-value Wald test: education, income, and marital status	0.335	0.201	-	-	0.128	0.685
p-value Wald test: BMI			0.361	0.051	0.292	0.063

Notes: The estimation results are based on the sample aged 50+ with respondents reporting equal survival probabilities excluded. N = 1,142; no. of failures = 277; standard errors given in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Chapter 3

Does respondent's knowledge on population life expectancy influence the accuracy of subjective survival probabilities?[18]

3.1. Introduction

Individuals' life expectancy plays an important role in long-term economic decisions such as retirement, savings and bequest decisions. Theoretical economic models of life cycle behavior such as Hurd (1989) have shown the importance of allowing for uncertainty in lifetime duration for economic outcomes. In household surveys, individual life expectancy is usually measured with questions about the probability of survival to a target age (Manski 2004). Empirical studies such as Gan *et al*. (2004) and Salm (2010) have included individuals' beliefs on life duration and conclude that individuals have private information about their own life expectancy on which they base their economic decisions. The existing literature, however, suggests that based on subjective survival probabilities (SSPs) most individuals underestimate their life expectancy (Perozek 2008; Steffen 2009; Teppa 2012; Groneck *et al.* 2013; Kutlu-Koc and Kalwij 2013). Underestimation of survival probabilities may have economic implications if individuals base their decisions on them. For example, those who think that they will not live until old age may not save enough to finance consumption during retirement. For the Netherlands, the country also analyzed in this paper, Kutlu-Koc and Kalwij (2013) find that 45 years old men and women, on average, underestimate their remaining life duration by about 1 and 8 years, respectively.

An important public policy issue we address in this paper is if the underestimation of individuals' life expectancy can perhaps be partly explained by their insufficient knowledge on population life expectancy. If, for instance, we find that people who underestimate population life expectancy also underestimate their own life expectancy, this would suggest that policymakers can improve individuals' economic decisions by providing information on population life expectancy.

Our contribution to the empirical literature is twofold. First, and most importantly, we investigate the extent to which individuals' knowledge on the population life expectancy

[18] This chapter is a joint work with Adriaan Kalwij.

affects the accuracy of their predicted life expectancy. For this we calculate subjective life expectancies based on two subjective probabilities of survival for each individual in our survey (see Kutlu-Koc and Kalwij, 2013 for details) and compare these with actual mortality experiences that we obtain from administrative records of the same individuals that are in the survey. We measure the respondent's knowledge on population statistics using questions about the average life expectancy in the Netherlands. The first question asks whether respondents have any idea about the average (population) life expectancy in the Netherlands. For those who answered the first question positively, the respondents are further asked to provide the age that they think people of their age and sex reach on average. We compare the answers to the second question with the population life expectancies from the age and gender specific period life tables. This comparison reveals the extent to which individuals' knowledge on the population life expectancy is in line with the actual life expectancy in the population. This information we relate to actual and subjective median remaining life duration.

Second, respondents often provide inconsistent answers to the subjective survival probabilities (SSPs) that are used to calculate subjective life expectancy. For instance, a survival probability to age 75 that is equal to or higher than the survival probability to age 70 violates (strict) monotonicity of the survival function.[19] While one can argue that equal SSPs are related to rounding, this would require making additional assumptions to incorporate such observations in an empirical analysis. An alternative is to drop such observations and estimate a subjective mortality risk model using only individuals who provided consistent answers. This latter approach is only valid when excluding inconsistent responses does not yield a selection bias. A selection bias might, however, occur if those who were unable to answer these questions consistently may also have a different subjective (and possibly objective) mortality risk. We, therefore, control for possible selection bias by estimating a selection model similar to the one proposed by Heckman (1979). The model is identified by using information on respondents' inability to answer questions about income expectations as a proxy for their knowledge of the laws of probability.

Previous studies suggest that respondent's knowledge on population statistics may affect the responses that are given to probabilistic questions. Using the Retirement

[19] For example, the study by Kutlu-Koc and Kalwij (2013) shows that around 32 percent of the respondents from the Dutch Household Survey reported equal survival probabilities for two target ages, while about 0.63 percent indicated a survival chance to the earlier target age that is less than their survival chance to the later target age.

Perspectives Survey on older Americans McFadden *et al.* (2004) show that respondents' probability of being admitted to a nursing home is affected by the population information on the fraction of Americans admitted to nursing homes. In their study respondents who answered a question and at the same time received information about the fraction of people admitted to nursing homes in the beginning of the survey reported, on average, a lower subjective probability of being admitted to a nursing home compared to the respondents who did not receive that information.

Using the German SAVE survey, Steffen (2009) finds that both German men and women underestimate their life expectancy compared to actuarial life expectancy. He calculates subjective life expectancy by combining questions about average life expectancy and respondents' subjective position relative to the average. His findings suggest that a large fraction of the sample expects to live about as long as the average. The reported average life expectancy is, however, significantly lower than the actuarial life expectancy which suggests that underestimation of subjective life expectancy is mainly caused by individuals' underestimation of population life expectancy. In our study we measure subjective life expectancy with individuals' answers to survival probability questions. The advantage of using SSPs is that they can be directly linked to life cycle models which make use of subjective probabilities. Another difference between his study and ours is that his analyses are based on actuarial life tables since he does not observe actual mortality. In our study we compare individuals' life expectancy with the observed (actual) life duration within the sample. Moreover, the first question in our survey, which is not available in the SAVE survey, allows us to distinguish those who do not know population life expectancy.

For our analysis we use data from the 1995 and 1996 DNB Household Survey (DHS) supplemented with (administrative) data on actual mortality from the causes of death registry over the period 1995-2010. Regarding sample selection, we find that the removal of individuals with inconsistent answers to probabilistic survival questions does not lead to biased coefficient estimates in the subjective mortality risk model. Our main result is that knowledge on population life expectancy significantly helps individuals predict their remaining lifetime more accurately and that individuals' underestimation of population life expectancy significantly explains the underestimation of their remaining lifetime.

The paper is structured as follows: Section 3.2 describes the data. Section 3.3 outlines the mortality risk model and the methods for its estimation using objective (actual) and then subjective survival data. Section 3.4 presents the estimation results, and Section 3.5 offers our concluding remarks.

3.2 Data

This paper combines survey data with individual-level administrative data to compare survival expectations of the Dutch with their actual mortality (i.e., date of death). The SSPs (subjective survival probabilities) are taken from the 1995 and 1996 waves of the DNB Household Survey (DHS), begun in 1993 and originally known as the CentER Savings Survey (see Kutlu-Koc and Kalwij 2013 for a detailed description). Every year, all household members aged 16 or over are interviewed online. Those who do not have a computer and/or Internet access are provided with these tools by the survey agency.

The data on the actual mortality of survey respondents are taken from the Dutch causes of death registry (DO, DoodsOorzaken) survey, which records the date of death of all residents deceased during the 1995–2010 period. These data are provided by medical examiners, who are legally obliged to submit them to Statistics Netherlands. The DO dataset also assigns a personal identifier that matches the personal identifier in the DHS, thereby allowing determination of whether individuals in the 1995 or 1996 wave of the DHS were still alive at the end of the observation period (December 31, 2010) or whether they had died, and if so, on which date.

Subjective survival probabilities are measured in the DHS by the following survey question:

- *How big do you think is the chance that you will attain (at least) the age of T?*

where $T \in \{75, 80, 85, 90, 95, 100\}$ is a target age that depends on the respondent's current age.

Respondents aged 25 through 65 report their probability of survival to age 75 and age 80; those aged 65 through 70, their survival expectations to age 80 and age 85; and respondents aged 70–75, 75–80, and 80–85, their expected survival probabilities to 85 and 90, 90 and 95, 95 and 100, respectively. The responses are measured on a 10-point scale, from 0, "no chance at all," to 10, "absolutely certain." Following Hurd and McGarry (1995), we assume that after being divided by 10, the responses can be interpreted as probabilities conditional on being alive at a certain age.[20]

[20] Following Perozek (2008), we replace probabilities 0 and 1 with 0.01 and 0.99, respectively, for computational reasons. Our main findings remain when we either replace the probabilities 0 and 1 with 0.05 and 0.95, respectively, or by excluding 0 and 1 answers from the analysis (results are available upon request).

The DHS survey additionally contains two questions about average life expectancy in the Netherlands. The first question is:

- *For people of your age and sex there is an average life expectancy. Do you have any idea what age people of your age and sex reach on average?*

The answer to this question can be either yes or no. To respondents who answered yes, the following question is asked to elicit their beliefs about population life expectancy:

- *What age do you think people of your age and sex reach on average?*

The reported ages in this question are compared to the corresponding population life expectancy from the age and gender specific 1995 life table available in the Human Mortality Database (HMD). We create two variables based on the responses given to these two questions. The variable 'Does not know population life expectancy' takes one if someone said no in the first question about average life expectancy. The variable 'Reported minus life table life expectancy' is defined as the difference between someone's beliefs about population life expectancy in the second question and his/her actuarial life expectancy. The latter is missing for the individuals who said no in the first question, therefore, we assign zero to this difference if individuals have no idea about the average life expectancy in the Netherlands (for which we control in our analysis).

We measure respondents' knowledge of the laws of probability using the following questions about income expectations:

- *What do you think is the probability that the total net income of your household will be less than €[LOWEST+(HIGHEST-LOWEST)*{0.2/0.4/0.6/0.8}] in the next 12 months?*

where LOWEST and HIGHEST are the minimum and maximum values of total net expected household income reported by the respondents, respectively. Respondents receive four questions consecutively where they are asked to report the probability that their total net annual household income will be less than 20/40/60/80 percent above their lowest expected yearly income. If respondents' answers satisfy the laws of probability we expect to find that these probabilities are increasing with the threshold level, that is, if respondents' income is less than 20 percent above their lowest expected income it is also less than 40 percent above their lowest expected income. We create a dummy variable called 'Not able to answer probabilistic questions on future income' which takes one if the respondent's answer does not satisfy this property.

The definitions of all other variables used in our analysis are listed in section 3.A.

3.2.1 Sample Selection

Individuals aged 25 and above are included in our sample.[21] If respondents were observed in both the 1995 and 1996 waves, we use only the earlier response to avoid the potential influence of repeated interviewing on respondent behavior (Lazarsfeld 1940; Sturgis *et al.* 2009).

At baseline, the sample includes 5,573 observations and we are forced to drop 3,328 observations (59.7 percent of the initial sample) because information is missing for one of the covariates under study. We test if individuals in our final sample have the same mortality risk as those excluded from the estimations. The *p-value* corresponding to the hypothesis test of equal mortality risks for the two groups is equal to 0.128, suggesting that the sample selection is not endogenous with respect to mortality.

3.2.2 Descriptive Statistics

For the analysis of subjective mortality risk we make use of two SSPs for each individual. Not all respondents provide two SPPs that can be used in the analysis. If, for instance, a respondent answers that his survival probability to age 75 is less than or equal to his survival probability to age 80, this violates a strict monotonicity assumption (i.e. the survival up to age 75 should be larger than the survival up to age 80). According to Table 3.1, 601 respondents in our sample provided answers that violate the strict monotonicity assumption.

Among these respondents 584 of them (not reported in Table 3.1) provided equal survival probabilities for two target ages suggesting that the majority of the inconsistent answers are due to equal survival probabilities. As will be explained in the next section, in the empirical analysis the tendency to provide inconsistent answers to SSPs will be taken into account. Table 3.1 shows respondent characteristics for two samples: a sample with 1,644 respondents who provide consistent answers to SSPs and a sample with 601 respondents who provide inconsistent answers to SSPs. In this way we also obtain some preliminary insights into the issue how the ability to give consistent answers to SSPs is related to individuals' characteristics.

[21] Because many individuals under 25 are still enrolled in education, their individual income and (final) educational level are unavailable. We use observations of the head of household and the spouse/permanent partner only since questions about population life expectancy were not posed to other members of the household. We run a robustness test by using a different age group (a sample of individuals older than 50) and our main results are to a large extent unchanged (see Table 3.B.1, section 3.B).

Table 3.1: Descriptive statistics explanatory variables. SSP=Subjective Survival Probability

	Sample with consistent answers to SSPs	Sample with inconsistent answers to SSPs
Number of observations	1,644	601
Reported minus life table life expectancy (conditional on knowing population life expectancy)		
Mean	-2.56	-2.41
25th percentile	-4.68	-4.72
Median	-2.56	-2.08
75th percentile	-0.69	-0.35
Proportions	%	%
Does not know population life expectancy	20.19	26.29
Not able to answer probabilistic questions on future income	58.64	67.72
Happy	86.50	87.85
Female	36.25	41.76
Low education	18.67	23.46
Medium education	32.24	39.60
High education	49.09	36.94
Standardized income tertile 1st	33.03	39.60
Standardized income tertile 2nd	27.80	26.46
Standardized income tertile 3rd	39.17	33.94
Married	87.77	88.35
Divorced	3.71	3.00
Widowed	2.01	2.33
Single	6.51	6.32
Chronic illness	23.24	24.29
No smoking	69.28	70.72
Alcohol	8.88	7.65
Good health	82.97	86.52
Normal weight	60.34	58.74
Overweight	34.49	36.44
Obese	5.17	4.83
Mortality rate	11.98	8.82
	Years	Years
Median life duration (conditional on mortality=1)	75.50	74.92
Average objective life expectancy [a]	84.97	85.23
Average subjective life expectancy [b]	80.69	-
Average age	47	47

Notes: [a] The objective life expectancy is computed based on the estimation of a Gompertz mortality model with only gender, age, and the year of birth as covariates. [b] Based on SSPs and assuming a Gompertz mortality model.

The first panel in Table 3.1 shows the distribution of the difference between beliefs about population life expectancy and actuarial life expectancy. The mean difference is -2.56 years for the individuals who provided consistent answers to SSPs whereas it is -2.41 years for the individuals who could not answer questions about SSPs consistently and both differences are statistically significant (not reported in Table 3.1). Median differences are also negative, implying that the majority of the respondents reported an average life expectancy which is lower than the actuarial life expectancy. These findings suggest that most individuals are not well-informed about the population statistics and they underestimate the actual life expectancy in the population. Note that when we calculate the difference between beliefs about population life expectancy and actuarial life expectancy, we are forced to use period life tables since cohort life tables are not available for each individual in our sample. It is known that period life tables tend to underestimate life expectancy compared to cohort life tables when mortality rates decline over time (See, e.g., Hurd and McGarry 1995, 2002). As a result, the distribution of the difference variable would shift to the left and we would expect the difference to be more negative if we used cohort life tables rather than period life tables. In other words, on average, the underestimation of population life expectancy seems to have little to do with the difference between period and cohort life tables.

Table 3.1 also displays that those who do not know the average life expectancy in the Netherlands give 26.29 percent of the inconsistent answers to survival probability questions as opposed to 20.19 percent of consistent answers, suggesting that having knowledge of population life expectancy may play a role in being able to answer probabilistic survival questions correctly. 67.72 percent of inconsistent answers are given by the respondents who are unable to answer probabilistic questions on future income whereas the same respondents give 58.64 percent of consistent answers. This suggests that having probabilistic knowledge is associated with being able to provide consistent answers to SSPs. Table 3.1 also reveals that the ability to answer survival probability questions consistently is related to gender and socioeconomic factors such as level of education and income. Respondents who are in good health provide 86.52 percent of inconsistent answers whereas the same respondents give 82.97 percent of consistent answers which indicates that being able to answer survival probability questions consistently is negatively correlated with the self-reported health status of the respondents. The average objective median life duration (based on a Gompertz mortality model) is around 85 years for respondents in our sample whereas their subjective median life duration calculated from subjective survival probabilities is 80.69 years, on average.[22] The median life duration for those who die during the observation period is around 75 years, indicating that half of the respondents survived up to age 75. The observed median life duration for those who died during the 1995-2010 sample period (for 250 individuals) is lower than the average median

[22] Using the respondents' subjective survival probabilities, we compute the subjective median life duration conditional on baseline age for each individual in the sample (Kutlu-Koc and Kalwij 2013).

life duration based on a prediction of a Gompertz mortality model because the latter also takes into account those who are still alive at the end of the observation period which are the relatively more healthy respondents.

3.3 Estimation methodology

Following previous empirical studies on individual mortality, we assume that life duration can be modeled with a (truncated) Gompertz distribution (see, e.g., Gompertz 1825; Olshansky and Carnes 1997; Perozek 2008). This assumption makes it possible to compare predicted life durations based on the subjective and objective mortality models for groups of individuals who differ with respect to observed characteristics such as their knowledge on population life expectancy.

3.3.1 Objective Mortality Model

In this section we outline a proportional hazard rate model for investigating the extent to which actual mortality risk within the sample is associated with knowledge on the population life expectancy and a set of controls.

Assuming that respondent i is aged t_0 when he reports his probability of survival to age t, and T is a random variable representing the respondent's age at death, then the survival function, which gives the probability of the respondents' age at death being greater than t, can be written as follows:

$$S(t|\mathbf{x_i}) = \Pr\left(T > t|t_0, \mathbf{x_i}\right) = \exp\left\{-\int_{t_0}^{t} \theta(s|\mathbf{x_i})ds\right\} = \exp\left(-\Lambda_{t_0}(t|\mathbf{x_i})\right), \tag{3.1}$$

where $\theta(t|\mathbf{x_i})$ is the hazard function of the respondent with characteristics $\mathbf{x_i}$ and $\Lambda_{t_0}(t|\mathbf{x_i})$ is the integrated hazard from age t_0 to age t. Assuming that the random variable T follows a Gompertz distribution, the hazard function can be given by

$$\theta(t|\mathbf{x_i}) = \exp\{\gamma_O t + \mathbf{x_i}\boldsymbol{\beta_O}\} \tag{3.2}$$

Each respondent is observed first at age $t_{0,i}$. The density function of dying at age t_i is $S(t_i|\mathbf{x_i})\theta(t_i|\mathbf{x_i})$ and the probability of a respondent still being alive at the end of observation period (where t_i is December 2010) is given by the survivor function $S(t_i|\mathbf{x_i})$.

Based on these ingredients we can obtain the estimates $\hat{\boldsymbol{\beta}}_{\mathbf{O}}$ and $\hat{\gamma}_O$ by using maximum likelihood (Lancaster, 1990).

3.3.2 Subjective Mortality Model

In this section we outline a selection model similar to Heckman (1979) for investigating the link between subjective mortality risk and knowledge on the population life expectancy. This model takes into account possible endogenous sample selection that might occur because subjective mortality risk can only be calculated for individuals who provided consistent answers to survival probabilities.

The first part of the model is the selection equation:

$$C_i = \begin{cases} 0 & if \quad u_i \le -\mathbf{w_i}\boldsymbol{\alpha} \\ 1 & if \quad u_i > -\mathbf{w_i}\boldsymbol{\alpha} \end{cases} \tag{3.3}$$

where C_i is equal to one if the respondent provided (two) consistent SPPs, and zero otherwise. We assume u_i is identically and normally distributed. If C_i is equal to one, we estimate, based on two SSPs, the parameters of subjective mortality model using nonlinear least squares (NLLS) as follows[23]:

$$SSP_{j,i} = S_{j,i}\left(\gamma_S, \lambda_S \middle| t_{0,i}, t_{j,i}\right) + \rho IMR_i + \varepsilon_{j,i} \qquad j \in \{1,2\}, \quad i = 1,..., N \tag{3.4}$$

with $S_{j,i}\left(\gamma_S, \lambda_S \middle| t_{0,i}, t_{j,i}\right) = \exp\left\{\frac{\lambda_S}{\gamma_S}\left(\exp\{\gamma_S t_{0,i}\} - \exp\{\gamma_S t_{j,i}\}\right)\right\}$ and $\lambda_S = \exp\{\mathbf{x_i}\boldsymbol{\beta}_S\}$

where $SSP_{j,i}$ are subjective survival probabilities and $t_{j,i}$ are the corresponding target ages, $t_{0,i}$ is the age when individuals report their probability of survival and $\varepsilon_{j,i}$ is an error term that is identically (also across j) and normally distributed. IMR_i stands for the inverse Mills ratio which is added to control for possible sample selection. We use a two-step estimation procedure for estimating equations (3.3) and (3.4).

[23] The hazard rate is given by $\theta(t|\mathbf{x_i}) = \lambda_i \exp\{\gamma_i t\}$, with $\lambda_i = \lambda_S = \exp\{\mathbf{x_i}\boldsymbol{\beta}_S\}$ and $\gamma_i = \gamma_S$.

In the first step we obtain the estimates $\hat{\boldsymbol{\alpha}}$ after a Probit estimation and use this to calculate the inverse Mills ratio (IMR_i)[24]. In the second step, the estimated inverse Mills ratio is added to the equation (3.4) as an explanatory variable this equation is estimated using the NLLS.[25]

The NLLS estimates of γ_S^*, λ_S^*, ρ^* are obtained by minimizing the following expression:

$$\min_{\gamma_S, \lambda_S, \rho} \sum_{i=1}^{N} \left(\sum_j \left(SSP_{j,i} - S_{j,i}\left(\gamma_S, \lambda_S \middle| t_{0,i}, t_{j,i}\right) - \rho IMR_i \right)^2 \right) \tag{3.5}$$

3.3.3 Empirical specifications

In the models outlined the row vector $\mathbf{x_i}$ contains the variables related to knowledge on population life expectancy, gender, educational attainment, household income, marital status and whether or not the individual has a chronic illness and self-assessed health status. We control for mood-effect when answering SSPs using reported happiness at the time of the survey (variable "happy"). In addition we control for behavioral health risk using variables related to smoking, alcohol consumption and BMI. The definitions of all variables are in section 3.A.

The reason for giving inconsistent answers to SSPs can be related to individuals' knowledge on population life expectancy or their more general inability or unwillingness to answer probabilistic questions. This, in turn, might be related to individual's life duration and may therefore result in a possible selection bias. As discussed and outlined above, we take this into account by estimating a selection model (Heckman, 1979) and identify this model by using the variable as 'not able to answer probabilistic questions on future income' (see section 3.2). In the models outlined above this variable is included in the $\mathbf{w_i}$ but excluded from $\mathbf{x_i}$. With this so-called exclusion restriction needed for model identification, we assume that ability to answer the income expectation questions

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[24] $IMR_i = \dfrac{\phi\left(\mathbf{w_i}\hat{\boldsymbol{\alpha}}\right)}{\Phi\left(\mathbf{w_i}\hat{\boldsymbol{\alpha}}\right)}$ where $\phi(.)$ and $\Phi(.)$ are the standard normal density and cumulative density functions, respectively.

[25] We compute bootstrapped standard errors with 1000 replications. More explicitly, we bootstrap the coefficient estimates of both first stage and second stage equations by resampling observations (with replacement) from our sample 1000 times and calculate the standard errors.

consistently does not affect individual's subjective survival once the variables included in $\mathbf{x}_i$ are controlled for.

3.4 Empirical Results

We first estimate the selection equation as described in Section 3.3.2. This equation relates a binary indicator of being able to provide consistent answers to SSPs to variables measuring respondents' knowledge on population life expectancy, being unable to answer probabilistic questions on future income, and the other individual characteristics. Table 3.2 gives parameter estimates, standard errors, and marginal effects after a Probit estimation.

According to the results in Table 3.2, the coefficient on being unable to answer probabilistic questions on future income is negative and statistically significant, suggesting that those who cannot answer the probabilistic questions on income consistently are less likely to provide consistent answers to SSPs than those who are able to answer the income questions consistently. In other words, having knowledge of the laws of probability may play an important role in being able to answer probabilistic questions correctly.

We also find that the answers that are given by respondents who do not have any idea about population life expectancy are not significantly different than the answers reported by those who have an idea about it. Similarly, the difference between respondents' beliefs about population life expectancy and the actuarial life expectancy does not significantly affect the ability to answer survival probability questions correctly. Overall, the *p-value* of the Wald test for knowledge also indicates that the coefficients of two variables measuring respondents' knowledge on population life expectancy are not jointly significant at a 5 percent level of significance, implying that respondents' knowledge on population life expectancy does not play a major role in answering probabilistic survival questions correctly.

This model also shows that high educated are more likely to provide consistent answers to SSPs than medium educated. The marginal effect of having high education on the probability of giving consistent answers to SSPs shows that an average high educated respondent is about 8 percentage points more likely to provide a consistent answer to survival probability questions compared to an average medium educated person. Compared to the average rate of giving consistent answers to SSPs in the sample which is about 73 percent, the size of the marginal effect is not negligible. Moreover, the *p-value* of the Wald test shows that the coefficients of low and high education are jointly significant at a 1 percent level of significance. In terms of self-rated health status the results suggest that respondents who are in good health are less likely to provide consistent answers compared to respondents who are not in good health.

Table 3.2: Estimation results of the selection equation (First stage Heckman)

Dependent variable: Being able to answer probabilistic survival questions consistently	Parameter estimate	Standard error	Marginal effect [a]
Does not know population life expectancy	-0.085	0.074	-0.028
Reported minus life table life expectancy	-0.013	0.009	-0.004
Not able to answer probabilistic questions on future income	-0.208***	0.061	-0.067***
Happy	-0.034	0.089	-0.011
Female	-0.104	0.064	-0.034
Birth year	-0.014	0.051	-0.004
Age (in months and years)	-0.013	0.051	-0.004
Low education	-0.023	0.079	-0.007
High education	0.242***	0.068	0.078***
Standardized income tertile 1st	-0.053	0.075	-0.017
Standardized income tertile 3rd	0.031	0.074	0.010
Divorced	0.129	0.162	0.041
Widowed	-0.061	0.205	-0.020
Single	0.047	0.121	0.015
Chronic illness	-0.122	0.079	-0.041
No smoking	-0.059	0.064	-0.019
Alcohol	0.042	0.107	0.013
Good health	-0.271***	0.095	-0.083***
Overweight	-0.050	0.062	-0.016
Obese	0.054	0.135	0.017
Constant	30.372	101.406	
Number of observations	2,245		
p-value Wald test: knowledge	0.073		
p-value Wald test: education	0.000		
p-value Wald test: income	0.500		
p-value Wald test: marital status	0.831		
p-value Wald test: BMI	0.616		

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a] The marginal effect on the probability of being able to answer probabilistic survival questions consistently.

Table 3.3 reports the estimation results for the subjective mortality model with or without controlling for endogenous sample selection and for the objective mortality model.

Table 3.3: Estimation Results for the Objective and Subjective Mortality Risk Models

	Objective (1)	Subjective (Heckman second stage) (2)	Subjective (no control for selection) (3)
Does not know population life expectancy	-0.132	0.142***	0.123***
	(0.177)	(0.031)	(0.028)
Reported minus life table life expectancy	0.026	-0.026***	-0.028***
	(0.021)	(0.004)	(0.004)
Happy	-0.215	-0.131***	-0.137***
	(0.173)	(0.032)	(0.031)
Female	-0.737***	-0.110***	-0.133***
	(0.168)	(0.028)	(0.024)
Birth year	0.010	0.002**	0.003*
	(0.015)	(0.001)	(0.001)
Low education	0.131	-0.106***	-0.110***
	(0.165)	(0.032)	(0.032)
High education	-0.232	-0.018	0.028
	(0.158)	(0.033)	(0.025)
Standardized income tertile 1st	-0.046	0.005	-0.007
	(0.180)	(0.028)	(0.027)
Standardized income tertile 3rd	-0.084	0.002	0.009
	(0.170)	(0.028)	(0.026)
Divorced	0.415	-0.026	-0.002
	(0.277)	(0.051)	(0.056)
Widowed	0.244	0.076	0.063
	(0.268)	(0.105)	(0.077)
Single	-0.174	-0.075*	-0.068
	(0.306)	(0.043)	(0.044)
Chronic illness	0.476***	0.093***	0.071**
	(0.156)	(0.034)	(0.028)
No smoking	-0.632***	-0.141***	-0.151***
	(0.143)	(0.024)	(0.023)
Alcohol	0.345*	0.053	0.058
	(0.209)	(0.039)	(0.036)
Good health	-0.286*	-0.222***	-0.268***
	(0.167)	(0.042)	(0.031)
Overweight	-0.137	0.044*	0.036
	(0.139)	(0.024)	(0.023)
Obese	0.304	0.092*	0.104**
	(0.235)	(0.052)	(0.047)
Constant	-31.236	-15.137***	-14.826***
	(31.064)	(2.767)	(2.838)
Age	0.010***	0.008***	0.008***
	(0.001)	(0.000)	(0.000)
Inverse Mills Ratio	-	0.122*	-
		(0.066)	
Number of observations	2,245	2,245	1,644
p-value Wald test: knowledge	0.419	0.000	0.000
p-value Wald test: education	0.104	0.004	0.000
p-value Wald test: income	0.883	0.979	0.821
p-value Wald test: marital status	0.328	0.305	0.367
p-value Wald test: BMI	0.182	0.057	0.044

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. 1000 replications are used to calculate bootstrapped standard errors in column (2).

The coefficient on the estimated inverse Mills ratio in column (2) is only statistically significant at a 10 percent significance level which suggests that endogenous sample selection is not a major concern in our subjective mortality risk model. Also the estimation results under columns (2) and (3) show that the estimates of the subjective mortality model without controlling for sample selection are similar to the ones after controlling for sample selection. These findings show that the removal of individuals with inconsistent answers to SSPs from the estimation does not lead to biased coefficient estimates of the subjective mortality risk model.

According to the results in column (1), knowledge on population life expectancy does not play a role in explaining objective (actual) mortality risk within the sample. Based on the subjective mortality model (column (2)), respondents who do not know population life expectancy have significantly higher subjective mortality risk compared to those who have an idea about population life expectancy. The coefficient on the difference between respondents' beliefs about population life expectancy and actuarial life expectancy is negative and statistically significant at a 1 percent level of significance. The subjective mortality risk is lower when the reported population life expectancy is greater than actuarial life expectancy, so individuals who overestimate the population life expectancy also report higher probabilities of survival. Conversely, the subjective mortality risk is higher when the difference is negative suggesting that individuals who underestimate population life expectancy also give lower probabilities of survival. These findings indicate that having knowledge on population life expectancy plays an important role in answering questions about survival probabilities.

The coefficient on being happy in the objective model is statistically insignificant whereas it is significant at 1 percent in the subjective model, suggesting that individuals' answers to SSPs may be influenced by their mood, that is, they may think that they will live longer when they feel happier.

Table 3.3 also shows that females have significantly lower subjective mortality risks than males although the coefficient on female in the subjective model is much smaller than that in the objective model. The findings also suggest that, less educated have significantly lower mortality risks than medium educated. On the other hand, the coefficient on low education in the objective mortality model suggests that low education live shorter than medium educated although it is not statistically significant. Finally, the coefficient on smoking in the subjective model is smaller than that in the objective model, indicating that individuals underestimate the risk from smoking.

KNOWLEDGE ON POPULATION LIFE EXPECTANCY

Next we investigate the extent to which individuals' knowledge on the population life expectancy explains the difference between subjective and objective remaining life expectancy. For this purpose we use the coefficient estimates in columns (1) and (3) of Table 3.3 to estimate the predicted median remaining life duration implied by objective and subjective mortality models for groups of individuals with different characteristics.[26] As a reference individual (or group) we take a 50-year old married man, born in 1945, living in a middle income household, who knows population life expectancy about right, is happy, in good health, a non-smoker and non-drinker, and has no chronic illnesses, and has normal weight and medium education.

According to the results in Table 3.4, for this reference 50-year old man the difference between subjective and objective predicted life durations is -1.10 years and not statistically significant. Next, we change one characteristic of this reference individual at a time and these results are reported in the remaining rows. For instance, we find a difference of -5.55 years for a 50-year old woman which suggests that women, on average, underestimate their remaining life duration compared to what is implied by the objective mortality model.

To test whether the difference between subjective and objective predictions is the same across characteristics we compare differences for each characteristic with the difference for the reference category and these are reported in column (5). The difference between 50-year old women and men suggests that women, on average, significantly underestimate their remaining lifetime about 4.45 years more than men. The reference category in Table 3.4 is a man who knows population life expectancy about right in the sense that his beliefs about population life expectancy coincides with the life expectancy obtained from the life table. The difference between beliefs about population life expectancy and actuarial life expectancy is set equal to one for the man who knows population life expectancy but overestimates it with one year, and it is set equal to minus one for the man who knows population life expectancy but underestimates it with one year.

According to the predictions in Table 3.4, men who do not know population life expectancy do not significantly underestimate their remaining lifetime, on average (third column). On the other hand, these men underestimate their remaining lifetime more than men who know population life expectancy about right (the reference) with a statistically significant difference of 2.35 years (column (5)).

[26] See section 2.A.2 for details.

Table 3.4: Comparison of Objective and Subjective Predicted Life Durations in years (means)[27]

Characteristics	objective (1)	subjective (2)	(2)-(1)	std. error	difference of differences (5)	std. error
Man (reference) [a]	33.80	32.69	-1.10	2.19	0.00	-
Woman	39.63	34.09	-5.55*	2.90	-4.45***	1.28
Man does not know PLE	34.87	31.42	-3.45	2.43	-2.35**	1.14
Man knows PLE but underestimates with one year	34.01	32.40	-1.61	2.20	-0.51***	0.13
Man knows PLE but overestimates with one year	33.59	32.99	-0.60	2.18	0.50***	0.13
Unhappy man	32.13	31.27	-0.86	2.29	0.24	1.06
Smoking man	28.79	31.11	2.33	1.89	3.43***	1.02
Obese man	31.38	31.61	0.22	2.36	1.32	1.37
Man in bad health	31.49	29.89	-1.60	2.26	-0.50	1.04
Man drinking alcohol	31.09	32.09	1.00	2.24	2.10	1.33
Man with chronic illnesses	29.99	31.93	1.95	1.97	3.05***	0.99
Low educated man	32.71	33.84	1.13	2.19	2.23**	0.99
High educated man	35.61	32.38	-3.23	2.43	-2.13**	1.04
Man living in a low income household	34.10	32.76	-1.35	2.32	-0.25	1.16
Man living in a high income household	34.49	32.60	-1.89	2.26	-0.79	1.06
Divorced man	30.45	32.70	2.25	2.47	3.35**	1.68
Widowed man	31.86	32.02	0.17	2.48	1.27	1.37
Single man	35.25	33.43	-1.83	2.93	-0.73	1.96

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a] The reference is a 50-year old married man, born in 1945, living in a middle income household who knows population life expectancy about right, who is happy, in good health, non-smoker, non-drinker, with no chronic illnesses, of normal weight and medium education. Standard errors are obtained by simulation techniques.

Table 3.4 also displays that men who know population life expectancy but underestimate it compared to actuarial life expectancy also underestimate their remaining lifetime by 1.61 years, although this difference is not statistically significant. This finding is in line with the study by Steffen (2009) which shows that German men and women who underestimate the population life expectancy also underestimate their own life expectancy compared to actuarial life expectancy, on average. Moreover, we also find that the level of underestimation by men who underestimate population life expectancy is 0.51 years higher than the level of underestimation by men who know population life expectancy about right

[27] We simulate the coefficient estimates of the objective and subjective models with 1000 replications and use the simulated estimates to calculate the difference between objective and subjective predicted remaining life durations. To find simulated coefficient estimates we first draw uniform random variables. We then find normally distributed random variables by using inverse CDF transformation and Cholesky decomposition (See, e.g., Law and Kelton 1982).

and this difference is statistically significant at 1 percent. This finding suggests that one year underestimation of population life expectancy is associated with 0.51 years more underestimation of respondents' own life expectancy, indicating the importance of having knowledge on population life expectancy when answering survival probability questions. Similarly, we find that one year overestimation of population life expectancy corresponds to 0.50 years more overestimation of respondents' own life expectancy.

Results in column (5) of Table 3.4 also show that male smokers significantly overestimate their remaining lifetime with about 3.4 years compared to male non-smokers. Similarly, those who have chronic illnesses overestimate their remaining lifetime with 3 years than those who do not have any chronic illnesses. We also observe that low educated overestimate and high educated underestimate their remaining lifetime compared to medium educated, respectively, suggesting that individuals' level of education does not help them predict their remaining lifetime more accurately. Finally, predictions regarding marital status indicate that divorced men significantly overestimate their remaining lifetime compared to married men.

3.5 Conclusions

In this paper we investigate the extent to which individuals' knowledge on the population life expectancy explains the differences between subjective and objective remaining life expectancies. We also control for endogenous sample selection that may result from respondents not answering survival probability questions consistently.

Our research produces several important findings. In our sample, drawn from the DNB Household Survey, individuals' ability to provide consistent answers to SSPs is affected by their knowledge of the laws of probability. The level of education plays a key role in giving correct answers to survival probability questions. Regarding sample selection, this paper finds that the removal of individuals with inconsistent answers to probabilistic survival questions does not lead to biased coefficient estimates of the subjective mortality risk model.

Our results regarding the difference between subjective and objective remaining life expectancy show that respondents' underestimation of population life expectancy significantly explains the underestimation of their remaining lifetime. The role of knowledge on population life expectancy in being able to answer the probabilistic survival questions accurately is large: a one-year more accurate prediction of population life expectancy is, on average, associated with about half a year more accurate prediction of one's own life expectancy.

Based on the findings of this paper it can be concluded that if individuals were better informed about the population life expectancies, the accuracy of their survival beliefs could improve considerably. As a result, a policy of providing respondents information about population life expectancies may help them making more optimal economic decisions such as saving and retirement decisions.

3.A Variable Definitions

Table 3.A.1: Variable Definitions

Variable	Description	Baseline
Happy	Respondent stated that he/she is very happy or happy in the question *'All in all, to what extent do you consider yourself a happy person?'*	The dummy variable 'happy' is equal to one if someone stated that he/she is very happy or happy, and zero otherwise.
Female	Respondent is female	Respondent is male
Low education	Respondent has primary/low level education or vocational training through the apprentice system	Respondent has pre-university education or junior/senior vocational training
High education	Respondent has a university degree or a vocational college degree.	Respondent has pre-university education or junior/senior vocational training
Standardized household income (in Dutch guilders)	The sum of the net annual incomes of all household members after deduction of taxes but before making payments such as rent, mortgages, etc. divided by the equivalence scale provided by Statistics Netherlands (Siermann *et al*., 2004) .	---
Lowest standardized income tercile	Respondent's standardized household income is lower than and equal to the 33th percentile of the standardized household income series	Respondent's standardized household income is between the 33th and 67th percentiles of standardized household income series
Highest standardized income tercile	Respondent's standardized household income is higher than and equal to the 67th percentile of the standardized household income series	Respondent's standardized household income is between the 33th and 67th percentiles of standardized household income series
Good health	Respondent's self-reported health is excellent/good	Respondent's self-reported health is fair/not so good/poor
No Smoking	Respondent is non-smoker	Respondent is smoker
Alcohol	Respondent consumes more than 4 alcoholic drinks a day	Respondent does not consume more than 4 alcoholic drinks a day
Chronic illness	Respondent suffers from long- term illness, disorder, disability, or the consequences of an accident	Respondent does not suffer from long-term illness, disorder, disability, or the consequences of an accident
Overweight	$25 \leq$ Respondent's body mass index (BMI) < 30	Respondent's BMI < 25
Obese	Respondent's BMI ≥ 30	Respondent's BMI < 25
Birth year	Respondent's year of birth	---
Single	Respondent is single	Respondent is married
Widowed	Respondent is widowed	Respondent is married
Age	Respondent's age in months at the time of interview	---

3.B Estimation results with individuals aged 50 and older

Table 3.B.1: Comparisons of Objective and Subjective Predicted Life Durations in years (means)

Characteristics	objective (1)	subjective (2)	(2)-(1)	std. error	difference of differences (5)	std. error
Man (reference) [a]	27.24	22.36	-4.88**	2.02	0.00	-
Woman	33.59	23.99	-9.60***	2.71	-4.72***	1.22
Man does not know PLE	29.83	21.09	-8.74***	2.37	-3.86***	1.02
Man knows PLE but underestimates with one year	27.62	22.09	-5.53***	2.05	-0.65***	0.11
Man knows PLE but overestimates with one year	26.87	22.64	-4.23**	1.99	0.65***	0.11
Unhappy man	25.79	21.22	-4.56**	2.14	0.32	0.93
Smoking man	23.90	21.53	-2.36	1.97	2.52***	0.84
Obese man	24.52	21.46	-3.06	2.26	1.82	1.10
Man in bad health	25.77	19.40	-6.38***	2.24	-1.50*	0.90
Man drinking alcohol	24.67	21.83	-2.84	2.12	2.04	1.26
Man with chronic illnesses	23.80	21.11	-2.68	1.89	2.20***	0.85
Low educated man	26.41	23.39	-3.02	2.08	1.86**	0.84
High educated man	28.32	21.60	-6.72***	2.20	-1.84**	0.90
Man living in a low income household	23.85	23.50	-0.35	1.18	4.53***	1.67
Man living in a high income household	25.90	23.77	-2.13	1.37	2.75*	1.66
Divorced man	23.89	23.02	-0.87	2.18	4.01***	1.55
Widowed man	24.45	21.27	-3.18	1.91*	1.70	1.39
Single man	28.46	23.87	-4.58**	2.23	0.30	1.87

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a] The reference is a 60-year old married man, born in 1935, living in a middle income household who knows population life expectancy about right, who is happy, in good health, non-smoker, non-drinker, with no chronic illnesses, of normal weight and medium education. Standard errors are obtained by simulation techniques. To test whether the difference between subjective and objective predictions is the same across characteristics, differences compared to the reference are computed and reported under the column (5).

Chapter 4
Consumption Behavior, Annuity Income and Mortality Risk of the Elderly[28]

4.1 Introduction

A simple life cycle model without uncertainty predicts that rational agents' level of consumption is determined by their lifetime income. Under the assumption that individuals' annual earned income is greater than their annual retirement income, this model implies that individuals save when they are young and draw down their assets after retirement. The existing literature shows that the prediction that wealth declines with age is not supported by the empirical evidence (See, e.g., Van Ooijen *et al*. 2014 and Poterba *et al*. 2011). These papers, among the others, find no evidence in favor of wealth decumulation by the elderly even at advanced ages. Extended versions of the life cycle model make attempts to explain this inconsistency. Hurd (1989, 1999) explains saving behavior of elderly singles and couples by adding uncertainty about the date of death and bequest motives. Hubbard *et al*. (1994) find that when uncertainty about lifetime, earnings and out-of-pocket medical expenditures are taken into account, the predictions of the model matches the observed trajectories of wealth and consumption more closely. Boersch-Supan and Stahl (1991) assume that the individuals' marginal utility of consumption is affected by their health status and, therefore, in their model individuals become consumption constrained due to deteriorating health in old age.

In this paper we aim to test the predictions of the life cycle models proposed by Hurd (1989, 1999). Hurd (1989) derives and estimates a model of consumption with mortality risk and bequest motives for elderly singles. This model predicts that the growth rate of consumption decreases as the mortality rate increases since individuals with higher mortality rates increase current consumption at the expense of future consumption. Hurd (1999) proposes a theoretical model to explain the consumption behavior of elderly

[28] This chapter is a joint work with Rob Alessie and Adriaan Kalwij.

couples. His model takes into account the mortality risk of both spouses and also allows for bequest motives and predicts that the growth rate of consumption declines as the mortality risk of the couple increases at advanced ages. For the US, and in line with this prediction, Salm (2010) finds that the consumption growth decreases with higher mortality rates for elderly singles. Using the two waves of the CAMS survey for the period 2001-2003, he shows that an increase in subjective mortality by 1 percentage point is associated with a decrease in consumption of nondurables by 1.8 percentage points.

Hurd (1989, 1999) focuses on retired individuals so that retirement decisions do not need to be explained. Models for couples and singles both predict that wealth profiles decline with age after retirement; therefore, we expect to see that total consumption is greater than annuity income unless individuals have a (strong) bequest motive. Additionally, the difference between total consumption and annuity income depends on the level of initial wealth, i.e. the higher the initial wealth, the higher the difference is.

Our contribution to the empirical literature is twofold. First, we test the models' predictions regarding the relation between wealth and the difference between total consumption and annuity income, a step not taken in previous studies. Second, we test the prediction regarding the consumption change and mortality risk for singles as well as couples. For this purpose we first extend the theoretical model of Hurd (1999) for couples and then estimate the model. For our analysis we use data taken from the Health and Retirement Study (HRS) supplemented with the Consumption and Activities Mail Survey (CAMS). In contrast with Salm (2010), we use five waves of the CAMS survey covering the years from 2001 to 2009. More importantly, we investigate as well whether the model's prediction holds for elderly couples.

The main findings of this paper are as follows: In line with theory we find that, on average, individuals' total consumption is greater than their annuity income after retirement and the difference between total consumption and annuity income increases with the wealth level. Our results also suggest that consumption growth decreases with higher mortality rates for elderly singles. On the other hand, for elderly couples, consumption growth does not respond to changes in the mortality risk of the couple.

The paper is structured as follows: Section 4.2 outlines the theoretical models. Section 4.3 describes the data and the descriptive statistics. Section 4.4 presents the estimation results, and Section 4.5 offers some concluding remarks.

4.2 Theoretical models

4.2.1 The Singles Model

Hurd (1989) analyzes a consumption model with mortality risk and bequest motives for elderly singles. The model includes only retired individuals so that retirement decisions do not have to be explained. Mortality risk is the only source of uncertainty. Households can hold private wealth and annuities to finance consumption during the period of retirement. Annuities are exogenously given and real annuity income is assumed to be constant over time.[29]

In addition, individuals face liquidity constraints. That is, the level of net worth is non-negative in each period and individuals enter retirement with a positive amount of assets. This assumption implies that individuals cannot borrow against future Social Security or pension income; therefore, private wealth and annuity wealth are not perfect substitutes. Hurd (1989) assumes that the consumers maximize the following expected utility function starting from the beginning of the retirement phase, $t=1$, until the certain time of death, $t=L$:

$$\sum_{\tau=t}^{L}(1+\rho)^{1-\tau}a_{\tau}^{t}u(c_{\tau})+\sum_{\tau=t}^{L}(1+\rho)^{-\tau}m_{\tau+1}^{t}V((1+r)A_{\tau}),\quad t=1,...,L \tag{4.1}$$

where $u(.)$ is an increasing, concave utility function, ρ is the rate of time preference, A_τ is the net worth at the end of period τ, a_{τ}^{t} is the probability that a person lives in period τ given that he/she survives the period t, $m_{\tau+1}^{t}$ is the probability that a person dies at the beginning of $\tau+1$ given that he/she survives the period t, $V(.)$ denotes the utility from bequests and it is increasing in A_τ, r is the real interest rate. In this model, the period at which the person dies is a random variable. L is the maximum age after which the person dies with certainty, i.e. $m_{L+1}^{L}=1$.

The first term in the objective function gives the expected discounted utility from consumption, c_τ, if the person is alive in period τ. The second term shows the expected discounted utility from leaving a bequest if the person dies at the beginning of period $\tau+1$. The utility of leaving a bequest is a function of the net worth at the beginning of period $\tau+1$, i.e. $(1+r)A_\tau$. The utility function in equation (4.1) is maximized subject to the following asset accumulation constraints and the liquidity constraints:

[29] In the United States, Social Security benefits are indexed for inflation whereas occupational pensions including defined benefit (DB) and defined contribution (DC) plans are not indexed for inflation.

$$A_t = (1+r)A_{t-1} + y - c_t\,, \quad t = 1,...,L \tag{4.2a}$$

$$A_t \geq 0\,, \qquad t = 1,...,L \tag{4.2b}$$

where y is the non-capital income (in real terms), consisting only of annuities which are assumed to be constant over time. If we ignore the liquidity constraints (4.2b), the first order condition of this maximization can be written as (see section 4.A.1 for the details):

$$u'(c_t) = \frac{1+r}{1+\rho}\left(\left(1-m_{t+1}^t\right)u'(c_{t+1}) + m_{t+1}^t V'\left((1+r)A_t\right)\right) \tag{4.3}$$

where $u'(.)$ is the marginal utility of consumption in period t, $V'(.)$ is the marginal utility of leaving a bequest in period t, m_{t+1}^t is the instantaneous mortality rate which is the probability that a person dies at the beginning of period $t+1$ given that he/she survives the previous period. Equation (4.3) is an Euler equation that describes the rule for the allocation of resources over time under lifetime uncertainty. According to this rule, the individual's marginal utility in period t, which depends on both consumption and leaving a bequest, is equal to the discounted expected marginal utility in period $t+1$. In case of a constant relative risk aversion (CRRA) utility function $u(c_t) = c_t^{1-\gamma}/(1-\gamma)$, and no bequest motive ($V'(.) = 0$) equation (4.3) becomes:

$$\left(\frac{c_{t+1}}{c_t}\right)^\gamma = \frac{1+r}{1+\rho}\left(1-m_{t+1}^t\right) \tag{4.4}$$

where γ is the coefficient of risk aversion. After taking the natural logarithm of both sides, equation (4.4) can be re-written as:

$$\Delta \ln c_{t+1} = \frac{1}{\gamma}\ln\left(\frac{1+r}{1+\rho}\right) + \frac{1}{\gamma}\ln\left(1-m_{t+1}^t\right) \tag{4.5}$$

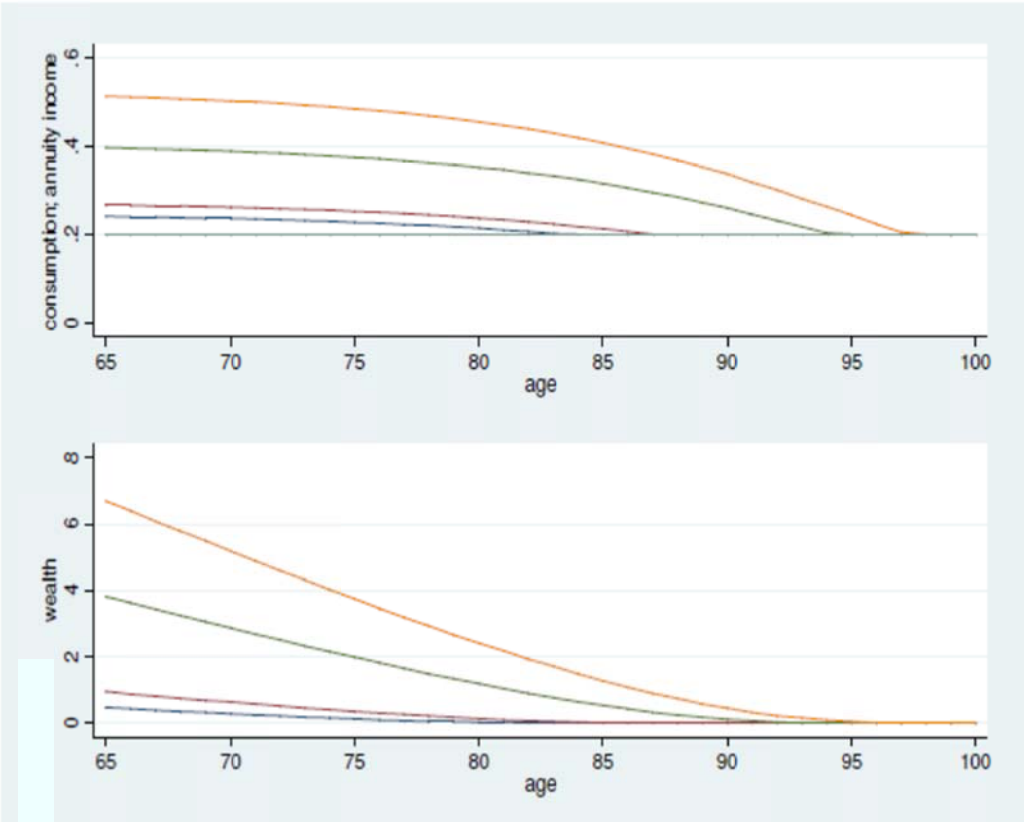
where $\Delta \ln c_{t+1} = \ln c_{t+1} - \ln c_t$. Equation (4.5) suggests that consumption growth increases with higher real interest rates while it decreases with higher rates of time preference and higher subjective mortality rates. If individuals are impatient ($\rho > r$), the consumption growth is negative since they prefer consuming today rather than consuming tomorrow. Since the survival probability declines exponentially with age, individuals behave even more impatient as they become older, and consumption declines at a faster rate. If individuals are more risk averse, the consumption path becomes flatter and consumption will decline slower with age.

This model assumes that individuals enter the retirement period with positive amount of assets, so that they are not liquidity constrained at the beginning of the retirement. However, they may become constrained at a certain period t ($A_t = 0, t = t_0,..,L$). In that case, consumption will be equal to annuity income from t_0 onwards. This is illustrated in Figure 4.1.

Figure 4.1

Consumption and wealth in a model without bequests: variation in A_0

(y=0.2; r=0.001; ρ=0.001; γ=4)



The flat line stands for the constant annuity stream after retirement. Individuals enter the retirement period at age 65 with positive amount of assets (level of initial wealth is positive). As they draw down their assets, they consume more than their annuity income. However, individuals may become constrained at a certain period and from this period onwards their consumption is equal to their annuity income. As a result, this model predicts that consumption is never smaller than annuity income, ($c_t \geq y$). This prediction still holds if we add additional uncertainty to the model such as uncertainty about out-of-pocket medical expenses (de Nardi *et al*., 2010). On the other hand, if people have a (strong) bequest motive, consumption may not exceed annuity income. This prediction also may not hold if the marginal utility of consumption depends on health status (Boersch-Supan and Stahl, 1991). Figure 4.1 also shows that different consumption profiles can be obtained for different levels of initial wealth. The level of consumption is an increasing function of initial wealth and the difference between total consumption and annuity income depends on the level of initial wealth, i.e. the higher the initial wealth, the higher the difference is. For high level of initial wealth the wealth-age profile is much steeper, suggesting that at the early stage of the retirement phase consumption is considerably larger than the annuity income. For low level of initial wealth the wealth-age profile is rather flat and individuals draw down their assets at a slow rate.

4.2.2 The Couples Model

Hurd (1999) proposes a consumption model with mortality risk and bequest motives for elderly couples. In this model the couple receives utility from consumption when both spouses are alive and from leaving bequests. There are two types of bequests. The wealth is first transferred to the surviving spouse and after the death of the surviving spouse; the wealth is inherited by children or others. This model is an extension of the singles model and the assumptions of the singles model are maintained. Both spouses are retired and the couple maximizes the following expected utility function starting from the beginning of the retirement phase, $t=1$, until the certain time of death of the surviving spouse, $t=L_{\max}$:

$$\sum_{\tau=t}^{L_{\min}}(1+\rho)^{1-\tau}a_\tau^t u(C_\tau)+\sum_{\tau=t}^{L_m}(1+\rho)^{-\tau}pm_{\tau+1}^t M((1+r)A_\tau)+\sum_{\tau=t}^{L_f}(1+\rho)^{-\tau}pf_{\tau+1}^t F((1+r)A_\tau)+ \\ \sum_{\tau=t}^{L_{\max}}(1+\rho)^{-\tau}h_{\tau+1}^t V((1+r)A_\tau) \qquad (4.6)$$

where $u(C_\tau)$ shows the couple's utility from consumption, ρ is the rate of time preference of the couple, a_τ^t is the probability that both spouses will be alive in period τ given that they survive the period t, $L_{\min}$ denotes the lifespan of the couple after which one of the spouses dies with certainty, A_τ is the net worth at the end of period τ, r is the real interest rate, $pm_{\tau+1}^t$ is the probability that the husband becomes a widower at the beginning of period $\tau+1$, L_m is the maximum lifespan of the husband, $pf_{\tau+1}^t$ is the probability that the wife becomes a widow at the beginning of period $\tau+1$, L_f is the maximum life span of the wife, $M((1+r)A_\tau)$ is the widower's utility of wealth, $F((1+r)A_\tau)$ is the widow's utility of wealth, $h_{\tau+1}^t$ is the probability that both spouses die at the beginning of period $\tau+1$, $V(.)$ is the utility from leaving bequests to the children or others, and $L_{\max}$ is the maximum lifespan of the surviving spouse.

The utility function in equation (4.6) is maximized subject to the asset accumulation constraints and the liquidity constraints as introduced in the singles problem:

$$A_t = (1+r)A_{t-1} + y - c_t\,,\ t = 1,...,L_{\max} \tag{4.7a}$$

$$A_t \geq 0\,, \qquad t = 1,...,L_{\max} \tag{4.7b}$$

The solution of this model depends on the widower's marginal utility of wealth, $M'((1+r)A_\tau)$, and the widow's marginal utility of wealth, $F'((1+r)A_\tau)$ (Hurd 1999, equation 5 on page 16). In order to estimate this model, one should explicitly define these marginal utilities. In this paper we aim to extend the model proposed by Hurd (1999) by deriving a unitary model for the couple. This model allows us to find a solution which is independent of the widower's and the widow's marginal utilities of wealth so that it can be estimated directly using the subjective survival probabilities of the husband and the wife. In our model the couple maximizes the following expected utility function starting from the beginning of the retirement phase, $t=1$, until the certain time of death of the surviving spouse, $t = L_{\max}$:

$$\sum_{\tau=t}^{L_{\min}} (1+\rho)^{1-\tau} a_\tau^t u\left(\frac{c_\tau}{\sqrt{2}}\right) + \sum_{\tau=t}^{L_m} (1+\rho)^{-\tau} pm_{\tau+1}^t M((1+r)A_\tau) + \sum_{\tau=t}^{L_f} (1+\rho)^{-\tau} pf_{\tau+1}^t F((1+r)A_\tau) + \sum_{\tau=t}^{L_{\max}} (1+\rho)^{-\tau} h_{\tau+1}^t V((1+r)A_\tau) \tag{4.8}$$

where $u\left(\frac{c_\tau}{\sqrt{2}}\right)$ shows the couple's utility from consumption divided by an equivalent scale (the often used OECD square root scale)[30], $M((1+r)A_\tau)$ is the widower's utility of wealth, i.e. $\sum_{\tau=t+1}^{L_m} (1+\rho)^{t+1-\tau} a_\tau^{m,t+1} u(c_\tau)$, $F((1+r)A_\tau)$ is the widow's utility of wealth, i.e. $\sum_{\tau=t+1}^{L_f} (1+\rho)^{t+1-\tau} a_\tau^{f,t+1} u(c_\tau)$. The utility function in equation (4.8) is maximized subject to the asset accumulation constraints and the liquidity constraints in (4.7a) and (4.7b).

In case of no bequest motive to the children or others and no liquidity constraints, we solve the couple's maximization problem and find the following Euler equation (see section 4.A.2 for the details):

$$u'\left(\frac{c_t}{\sqrt{2}}\right) = \left(\frac{1+r}{1+\rho}\right)\left[\left(1 - cm_{t+1}^t\right)u'\left(\frac{c_{t+1}}{\sqrt{2}}\right) + \sqrt{2}\left(pm_{t+1}^t + pf_{t+1}^t\right)u'(c_{t+1})\right] \tag{4.9}$$

---

[30] The OECD uses a scale which divides household income by the square root of household size when comparing income inequality and poverty across countries (e.g.OECD 2008).

where cm_{t+1}^{t} is the instantaneous mortality rate of the couple which is the probability that one of the spouses dies at the beginning of period $t+1$ given that both spouses were alive in the previous period. The mortality risk of the couple, cm_{t+1}^{t}, is the sum of mortality risk of the wife and mortality risk of the husband minus the probability that both spouses die in period $t+1$ given that both spouses were alive in the previous period.[31] pm_{t+1}^{t} is the probability that the husband becomes a widower at the beginning of period $t+1$ and it is equal to the probability that the wife dies at the beginning of $t+1$ times the probability that the husband survives the period t+1. Similarly, pf_{t+1}^{t} is the probability that the wife becomes a widow at the beginning of period $t+1$. Hurd (1999, p. 16) points out that the Euler equation does not include the marginal utility of leaving bequests to the children or others ,$V'(.)$, since the probability that both spouses dies in the near future is equal to zero. In case of a constant relative risk aversion (CRRA) utility function $u(c_t)=c_t^{1-\gamma}/(1-\gamma)$ for couples, equation (4.9) becomes:

$$\left(\frac{c_{t+1}}{c_t}\right)^{\gamma}=\frac{1+r}{1+\rho}\left[\left(1-cm_{t+1}^{t}\right)+\sqrt{2}^{1-\gamma}\left(pm_{t+1}^{t}+pf_{t+1}^{t}\right)\right] \tag{4.10}$$

By using this type of utility function, we implicitly assume that the husband and the wife have the same coefficient of risk aversion, γ. After taking the natural logarithm of both sides, equation (4.10) can be written as:

$$\Delta\ln c_{t+1}=\frac{1}{\gamma}\ln\left(\frac{1+r}{1+\rho}\right)+\frac{1}{\gamma}\ln\left[1-\left(cm_{t+1}^{t}-\sqrt{2}^{1-\gamma}\left(pm_{t+1}^{t}+pf_{t+1}^{t}\right)\right)\right] \tag{4.11}$$

$\Delta\ln c_{t+1}=\ln c_{t+1}-\ln c_t$. We call the term inside the logarithm, $cm_{t+1}^{t}-\sqrt{2}^{1-\gamma}\left(pm_{t+1}^{t}+pf_{t+1}^{t}\right)$, the couple's adjusted mortality rate and one can show that it is positive as long as the coefficient of risk aversion is larger than one and it increases with an increase in the mortality rates of the wife and the husband. Equation (4.11) shows, therefore, that the consumption growth of a couple is negatively related to the couple's adjusted mortality rate. As the mortality risk of the couple increases at advanced ages, we expect the consumption to decline with age. In the empirical part of this paper we assume that the coefficient of risk aversion is equal to 3, which is a reasonable value obtained by the

[31] We assume that the death of the husband is independent of the death of the wife.

previous studies (See, e.g., Palumbo 1999) and calculate the couple's adjusted mortality rate accordingly.[32]

4.3 Data

The HRS is a biennial panel survey of Americans and its respondents were first interviewed in 1992 (Juster and Suzman, 1995). The HRS is well-suited for the purpose of this study since it is a large sample of elderly population and it includes detailed information on employment status, annuity income, household wealth, marital status, subjective survival probabilities, and health status of the respondents and their spouses. The data on consumption come from the Consumption and Activities Mail Survey (CAMS) which is a supplemental survey to the HRS. In 2001 the CAMS survey sent questionnaires to a subsample of the households who were interviewed in the HRS 2000 core survey. If household members are married or have a partnership, the questionnaire was sent to one of the spouses, selected randomly. In the initial wave of the CAMS survey 3,866 households answered questions about household spending in 26 categories of nondurables and 6 categories of durables (see Hurd and Rohwedder, 2008 for details). This survey has smaller number of households than the HRS and covers the period from 2001 to 2011.

In this study we use five waves of the CAMS survey for the period from 2001 to 2009. The CAMS survey is matched to most of the information in the previous HRS wave, i.e. CAMS 2001 is matched to the HRS 2000. However, information on financial variables such as wealth and income can be obtained from the next HRS wave. For example, HRS 2002 collects information on total income for the year 2001 which coincides with the information on consumption in CAMS 2001.[33]

Individuals' annuity income (before-tax) is defined as the sum of income from employer pension and/or annuity, social security disability, supplemental security income, social security retirement, spouse or widow benefits, unemployment and worker's compensation, and other income including veteran's benefits, welfare and food stamps. After-tax annuity income is obtained by deducting total taxes paid (federal taxes, state taxes, and the Federal Insurance Contributions Act (FICA) tax which includes social security tax and Medicare tax) from before-tax annuity income. Federal taxes, state income taxes, and the FICA tax for each household in each year are calculated based on the NBER

[32] One can show that in this case the couple's adjusted mortality rate is equal to the average of wife's and husband's mortality rate.

[33] Since HRS 2012 is not available yet, we exclude CAMS 2011 from our analysis.

tax calculator, TAXSIM (see Feenberg and Coutts, 1993). This program calculates tax liabilities for these three categories for each household in our sample once we provide required information about the respondents such as their marital status, income from all sources, deductions etc.[34]

To measure individuals' mortality risk we use subjective mortality rates instead of life table mortality rates because of two reasons. Firstly, life table mortality rates do not show much individual variation since they are aggregated to allow only for differences by age, gender and race. Subjective mortality rates are correlated with individual characteristics such as level of education, wealth, and income, as well as behavioral factors such as smoking, alcohol consumption and obesity. Consequently, subjective mortality rates contain information which is not contained in life table mortality rates. Secondly, individuals make decisions based on their own chances of survival. For example, smokers may think that they would die earlier than an average person in the population and behave accordingly. In this case, life table mortality rates may not explain smokers' economic decisions.

Subjective mortality rates for each respondent and his/her spouse (if present) are calculated in each wave from 2000 to 2008 based on a question about individuals' probability of survival to a certain age. More explicitly, the HRS asks about respondents' self-reported probability of living to age T where T depends on the current age of the respondents and it is more than 10 years above the respondents' current age. The question is:

"[Using any] number from 0 to 100 where "0" means that you think there is absolutely no chance and "100" means that you think the event is absolutely sure to happen…What is the percent chance that you will live to be 80/85/90/95/100) or more?"

Hurd and McGarry (2002) show that these probabilities are good predictors of individuals' actual mortality within the sample and individuals who expect to live longer are less likely to die. Following Gan et al. (2003) and Salm (2010) we derive annual subjective mortality rates by assuming that individuals' subjective mortality rate ($m_{i,\tau}^{\tau-1}$) is proportionate to the life table mortality rate ($m_{0,\tau}^{\tau-1}$) as follows:

$$m_{i,\tau}^{\tau-1} = \xi_i m_{0,\tau}^{\tau-1} \qquad , \ \tau = t+1, t+2, ..., L+1 \qquad (4.12)$$

[34]For more information see http://hrsonline.isr.umich.edu/index.php?p=shownews3x1&hfyle=news198.

Under this assumption the subjective probability $s_{i,t,T}$ of individual *i* to survive from age *t* to age *T* can be shown as:

$$s_{i,t,T} = \prod_{\tau=t-1}^{T-1}(1-m_{i,\tau+1}^{\tau}) = \prod_{\tau=t-1}^{T-1}(1-\xi_i m_{0,\tau+1}^{\tau}) \tag{4.13}$$

Then individual mortality factor ξ_i in equation (4.12) is obtained by minimizing the following expression for each individual:

$$\min_{\xi_i}\left(s_{i,t,T} - \prod_{\tau=t-1}^{T-1}(1-\xi_i m_{0,\tau+1}^{\tau})\right)^2 \tag{4.14}$$

This method does not produce meaningful mortality factors if individuals reported zero or one answers to probability of survival to age *T*. To include these individuals in our analysis, we change the answers from 0 to 0.01 and 1 to 0.99, respectively. Life table mortality rates are taken from race, gender, and age specific life-tables of National Vital Statistics Reports which are available for the years from 2000 to 2008.

4.3.1 Sample selection

The CAMS survey has questions about household spending which are answered by the respondents who also participated in the HRS core survey in 2000. If two respondents are married or have a partnership, one of the spouses is selected randomly to answer the questions about household spending. We start with an unbalanced panel sample which includes 5,402 households who answered questions in the CAMS survey at least one year in the period from 2001-2009. We restrict the sample to 3,615 households in which the respondent and, if present, his/her spouse are aged 65 and over. Age 65 is the legal retirement age in the United States and at age 65 individuals become eligible for Medicare. Although most individuals are retired by the age of 65, we observe in the data that some individuals have income from earnings after age 65. Since we focus on retired individuals, we further restrict the sample to 3,264 households in which the respondent and, if present, his/her spouse do not earn any wage income. Next, we focus on individuals who are not liquidity constrained in the sense that they hold positive amount of household wealth in the first year they entered the survey. This restriction is necessary because we derive the Euler equations for singles and couples by assuming that there are no liquidity constraints. As a result, we estimate the Euler equations on a sample of individuals who are not liquidity constrained. After excluding households with zero or negative wealth holdings, we are left with 3,033 households. We further focus on 2,428 households which are single-person or two-person households.[35] In our sample a two-person household may become a one-person household during the observation period as a result of divorce, separation or the death of the spouse. However, we do not allow a one-person household to become a two-person household during the observation period. After excluding households who married or remarried during the observation period, we are left with 2,378 households. Next, we restrict the sample to 2,095 households in which the respondent and, if present, his/her spouse provided non-missing information on subjective survival probabilities. 1,183 households also have non-missing information on the change in nondurable consumption. Our final sample includes 1,154 households and 3,692 household-year observations with non-missing information on other covariates. Although we select households with positive level of wealth in the first year they entered the survey, for some households wealth is non-positive in the subsequent years. Among the 1,154 households with positive wealth in the first year of the survey, 54 of them have non-positive wealth in the subsequent years (4.68 percent). The models described above allow that individuals may become constrained at a certain period and from this period onwards consumption is equal to annuity income.

4.3.2 Descriptive Statistics

Table 4.1 displays the mean, median and standard deviation of some variables for the sample which includes both single and couple households.

Total consumption is the sum of durables and nondurables excluding spending on cars and mortgages.[36] Categories of durable consumption include refrigerator, washer/dryer, dishwasher, television, and computer and categories of nondurables are home insurance, property tax, rent, electricity, water, heat, home repair services, phone/cable/internet, auto insurance, health insurance, house/yard supplies, home repair supplies and services, food, dining out, clothing, gasoline, vehicle services, drugs, health services, medical supplies, vacations, tickets, hobbies, contributions, and gifts. Total consumption, after-tax annuity

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[35] For the one-person household, the household size is equal to one and the household member is separated/divorced/widowed or never married. For the two-person household, the household size is equal to two and the household members are married or living with a partner.

[36] These two spending categories contain components of savings. Individuals were asked to report total mortgage payments and total car payments which include both interest and principal. To find a pure spending measure for these two components, one needs to remove the saving component from the payments by subtracting the principle. Since the CAMS survey does not include information on principal and interest separately, we cannot calculate the pure spending measures for these components.

income, total net household wealth, total net financial wealth, and total health expenditures are measured at the household level. Total net household wealth excludes Individual Retirement Accounts (IRAs) and the value of 401k/Keogh plans and it is defined as the sum of all wealth components less all debt. The wealth components are the value of the primary residence, real estate, vehicles, stocks, checking accounts, government bonds, bonds, other wealth and the debt components are mortgages, home loans and other debt. Total net financial wealth does not include the value of the primary residence, real estate, mortgages, and home loans. Total health expenditures consist of expenditures on drugs, health services, medical supplies, and health insurance.

Table 4.1: Summary statistics (one-person or two-person households)

	mean	median	std. deviation
Total consumption (in 2003 dollars)	23380	18950	17240
Annuity income (in 2003 dollars)	18330	16090	13120
Wealth (in 2003 dollars)	289240	156730	590680
Financial wealth (in 2003 dollars)	151010	47510	356180
Total health expenditures (in 2003 dollars)	3510	2610	4100
Wealth/Annuity income	17.243	8.370	41.474
Financial wealth/Annuity income	8.974	2.418	27.982
Total consumption/Annuity income	1.632	1.133	2.119
Total consumption minus annuity income	0.498	0.206	2.017
Dummy (total consumption>=annuity income)	0.587	1	0.492
Age [a]	74.827	75	6.426
Male	0.324	0	0.468
Number of observations (households)	3,692 (1,154)		

[a] Age stands for the age of the respondent who answered the questions about the household consumption. For two-person households one of the spouses is chosen randomly to answer these questions. The variables measured at the household level are divided by the OECD-modified equivalence scale.[37]

According to Table 4.1, there is a difference between mean and median values for some variables such as total consumption, wealth, and financial wealth which may suggest that some households have very high levels of wealth and/or consumption. The mean ratio of wealth to annuity income is 17, which suggest that the sample has very wealthy households. On the other hand, the main component of wealth for the individuals aged 65 and older is housing wealth which is more difficult to liquidate. The mean ratio of financial wealth, which excludes housing wealth, to annuity income is 9 percent whereas the median

[37] This scale was proposed by Hagenaars *et al.*(1994) and it assigns a value of 1.5 to the households with two adults.

is around 2, showing that the majority of individuals have accumulated financial wealth when they were young. The ratio of total consumption to annuity income is larger than one which suggests that most individuals draw down their assets after retirement. This finding is reinforced by the mean value of the dummy variable which takes one if total consumption is greater than or equal to after-tax annuity income and zero otherwise. The mean value is 0.59 and median value is one for this variable. Table 4.1 also reveals that the proportion of men in the sample is 32 percent which suggests that women are over-represented in the sample. This finding is not surprising since the sample consists of individuals who are aged 65 and over and women live longer than men.

Table 4.2 shows the mean, median, and standard deviation of the variables used in the estimation of the Euler equation (equation (4.5)) for single households.

Table 4.2: Summary statistics (one-person households)

	mean	median	std. deviation
Nondurable consumption (in 2003 dollars) (all categories)	21992	17968	15381
Nondurable consumption (in 2003 dollars) (Salm (2010), sub-categories)	5911	4666	5820
Nondurable consumption growth ($\Delta \ln c_{t+1}$) (all categories)	-0.022	-0.022	0.266
Nondurable consumption growth (Salm (2010), sub-categories)	-0.042	-0.039	0.368
Subjective mortality rate ($m_{i,t}^{t-1}$)	0.058	0.034	0.055
Life table mortality rate ($m_{0,t}^{t-1}$)	0.047	0.039	0.030
Age	76.809	77	6.582
Male	0.212	0	0.408
Poor health	0.266	0	0.442
Good health	0.400	0	0.490
Years of education	12.517	12	2.475
Any ADL limitations	0.177	0	0.382
Any IADL limitations	0.369	0	0.482
CES-D score	1.566	1	1.877
Number of observations (households)	1,323(646)		

Notes: The number of observations is based on the estimation of the Euler equation. Since consumption expenditures are reported in every two years, the annual change in consumption growth is obtained by dividing biennial consumption growth rate into two.

We focus on nondurable consumption categories because these are easier to adjust for consumers compared to durable consumption categories. All categories of nondurable consumption are home insurance, property tax, rent, electricity, water, heat, home repair services, phone/cable/internet, auto insurance, health insurance, house/yard supplies, home repair supplies and services, food, dining out, clothing, gasoline, vehicle services, drugs, health services, medical supplies, vacations, tickets, hobbies, contributions, and gifts. The expenditures on some of these categories such as home insurance, property tax, rent, electricity, water, heat, and auto insurance are essential for individuals and we may not expect that they change in response to changes in the subjective mortality risk. Medical expenditures can be seen as an investment in health and may not provide direct utility to individuals. Salm (2010) uses seven categories of nondurables which are food, dining out, clothing, gasoline, vacations, tickets, hobbies. The latter categories are more easily adjusted in the response to changes in the subjective mortality risk. In the empirical part of the study we consider both all categories and the sub-categories of nondurables used by Salm (2010).

According to Table 4.2, the mean annual consumption growth in nondurable spending ($\Delta \ln c_{t+1}$) is negative which indicates that households' current consumption is higher than their consumption in the next year, on average. The mean of the subjective mortality risk ($m_{i,t}^{t-1}$) is 0.058 and the mean of the life table mortality risk ($m_{0,t}^{t-1}$) is 0.047, suggesting that individuals underestimate their survival probabilities compared to life table probabilities, on average. Good health is a binary indicator which takes one if individuals' self-rated health status is excellent and very good. Similarly, poor health is a dummy variable which is equal to one if individual's self-reported health is fair or poor. According to Table 4.2 the majority of the singles households are in medium or good health. "Any ADL limitations" is a binary indicator which shows whether individuals have any difficulty in activities of daily living such as eating, bathing, walking across a room, dressing, getting in and out of bed, and using the toilet. The variable "Any IADL limitations'' indicates whether individuals have any difficulty in Instrumental Activities of Daily Living task such as using a telephone, taking medication, handling money, shopping for groceries, preparing meals, and using a map. The sample statistics in Table 4.2 show that single individuals aged 65 and over are more likely to have IADL limitations than ADL limitations. The score on the Center for Epidemiologic Studies Depression (CES-D) is a mental health index which is commonly used by psychologists as well as economists (Hao, 2008; Finkelstein et al, 2008). The CES-D ranges from 0 to 8 and it is the sum of six negative indicators (depression, everything is an effort, sleep is restless, felt alone, felt sad, could not get going) minus two positive indicators (felt happy and enjoyed life); the higher the score, the more negative the respondent's feelings in the past week. According to Table 4.2, most individuals in the sample seem to be mentally healthy.

Table 4.3 gives descriptive statistics of the variables used in the estimation of the Euler equation (equation (4.11)) for couple households. Variables are defined as in Table 4.2.

Table 4.3: Summary statistics (two-person households)

	mean	median	std. deviation
Nondurable consumption (in 2003 dollars) (all categories)	34156	27996	23509
Nondurable consumption (in 2003 dollars) (Salm (2010), sub-categories)	10764	8870	8349
Nondurable consumption growth ($\Delta \ln c_{t+1}$) (all categories)	-0.038	-0.023	0.254
Nondurable consumption growth (Salm (2010), sub-categories)	-0.051	-0.052	0.318
Husband's subjective mortality rate	0.053	0.034	0.049
Wife's subjective mortality rate	0.041	0.025	0.045
The couple's adjusted mortality rate, subjective[a]	0.048	0.033	0.037
The couple's adjusted mortality rate from the life table[a]	0.040	0.034	0.020
Age_husband	75.784	75	5.216
Age_wife	73.287	73	5.034
Poor health_husband	0.224	0	0.417
Poor health_wife	0.199	0	0.400
Good health_husband	0.434	0	0.495
Good health_wife	0.441	0	0.496
Years of education_husband	12.991	12	3.116
Years of education_wife	12.792	12	2.311
Any ADL limitations_husband	0.111	0	0.314
Any ADL limitations_wife	0.119	0	0.324
Any IADL limitations_husband	0.344	0	0.475
Any IADL limitations_wife	0.263	0	0.440
CES-D score_husband	0.766	0	1.249
CES-D score_wife	1.048	0	1.521
Number of observations (households)	1,061 (524)		

Notes: The number of observations is based on the estimation of the Euler equation. Since consumption expenditures are reported in every two years, the annual change in consumption growth is obtained by dividing biennial consumption growth rate into two. [a] The coefficient of risk aversion is set equal to 3 to calculate the couple's adjusted mortality rate based on subjective probabilities and life table probabilities.

According to these statistics, subjective mortality rate of the husband, which is calculated using his self-reported probability of survival, is greater than that of the wife, suggesting that individuals are aware of the gender gap in life expectancy. The couple's adjusted mortality rate which is calculated based on subjective mortality risk of the husband and the wife is positive and it is very close to the couple's adjusted mortality rate obtained from the life table. Table 4.3 also reveals that husbands in the sample are two years older than their wives, on average. Another difference between husbands and wives comes from the health status in the sense that wives seem to be healthier than their husbands.

Table 4.4 reports the levels of total consumption and nondurable spending across years. According to Table 4.4, on average, both total and nondurable consumption have decreased over the years 2001-2009.

Table 4.4: Total consumption per household across years (in 2003 dollars) (equivalised)

		Total consumption		Nondurables		Nondurables (Salm (2010), sub-categories)	
year	No. Obs.	mean	median	mean	median	mean	Median
2001	583	25669	20064	25359	19605	7302	5339
2003	747	24955	20686	24619	20298	7134	5640
2005	826	22723	18155	22440	17968	6997	5229
2007	872	22789	18738	22400	18403	6758	5393
2009	664	20684	17500	20125	17312	5719	4821

Number of observations (households): 3,692 (1,154)

This pattern can be partly explained by the age effect. Individuals in the sample are becoming older over time and, therefore, they increase current consumption at the expense of future consumption. The decline in consumption from 2007 to 2009 could also be driven by the financial crisis which affected both the financial and housing wealth of the elderly.

Now, we check whether total consumption (or expenditures) exceeds after-tax annuity income for elderly singles and couples. Table 4.5 reports the mean of the dummy variable indicating that total consumption is greater than and equal to after-tax annuity income by different age groups in the sample.

Table 4.5: The mean of the dummy (consumption>=annuity income) by age groups

years from 2001 to 2009		
age class	mean	No. obs.
65-69	0.562	759
70-74	0.556	901
75-79	0.588	913
80-83	0.623	720
85+	0.641	399
Total	0.587	3,692

Income and expenditures are in 2003 dollars and divided by the OECD-modified equivalence scale.

According to Table 4.5 for the majority of the respondents total consumption is greater than their annuity income. Table 4.6 shows the proportions by age groups and years.

Table 4.6: The mean of the dummy (consumption>=annuity income) by age groups and years

	2001		2003	
age class	mean	No. obs.	mean	No. obs.
65-69	0.649	154	0.606	158
70-74	0.673	141	0.639	177
75-79	0.630	156	0.582	175
80-83	0.649	102	0.686	162
85+	0.657	30	0.723	75
	2005		2007	
age class	mean	No. obs.	mean	No. obs.
65-69	0.528	178	0.543	180
70-74	0.453	203	0.548	215
75-79	0.610	187	0.600	215
80-83	0.603	164	0.596	157
85+	0.638	94	0.622	105
	2009			
age class	mean	No. obs.		
65-69	0.426	89		
70-74	0.503	165		
75-79	0.516	180		
80-83	0.592	135		
85+	0.600	95		

Income and expenditures are is in 2003 dollars and divided by the OECD-modified equivalence scale. Age stands for the age of the respondent who answered the questions about the household consumption. For two-person households one of the spouses is chosen randomly to answer these questions.

These findings also suggest that the majority of the respondents spend more than their annuity income after retirement, although there are some differences across years. For example, in 2009 we find that most respondents in the age groups 65-69 spent less than their annuity income. The drop in consumption in this particular year could reflect the effect of the global financial crisis. Due to a strong stock market decline in 2009 individuals who just entered retirement might experience a loss in their financial assets, which might cause them to consume less than their annuity income. Table 4.6 also shows that the proportions in 2009 are smaller than those in 2001, which may suggest that younger cohorts have fewer assets than older cohorts.

4.4 Estimation Results

In the previous section we find that more than half of the individuals in our sample spend more than their annuity income after retirement which indicates most individuals have decreasing wealth profiles in old age. The models that we outlined in Section 4.2 also predict that the difference between total consumption and annuity income is larger if the level of initial wealth is higher (see Figure 4.1 in Section 4.2). In this section we first test whether this prediction holds.

Table 4.7 gives the estimation results by the Ordinary Least Squares (OLS) for single households. The dependent variable is the logarithm of total consumption minus logarithm of annuity income in models reported under the first two columns. According to the results under the first column, the coefficient of wealth is positive and statistically significant, suggesting that the higher the level of wealth, the larger the difference between total consumption and annuity income is. In other words, individuals (or single households) are more likely to spend more than their annuity income as the level of their assets increases. The results also indicate a significant age effect. As individuals draw down their assets after retirement, their total consumption converges to annuity income at advanced ages. Another interesting finding is that level of education is positively associated with the difference between total consumption and annuity income. This may suggest that high educated receive a higher salary than low educated and, in turn, they accumulate more assets when they are young. As a result, high educated are able to spend more than their annuity income after retirement.

Table 4.7: Estimation results based on the OLS (one-person households)

	(1) Log total consumption minus log annuity income	(2) Log total consumption minus log annuity income	(3) Log total consumption (excluding health exp.) minus log annuity income	(4) Log total health expenditures
Year of birth	-0.023***	-0.022***	-0.016***	-0.051***
	(0.005)	(0.005)	(0.005)	(0.009)
Age	-0.019***	-0.018***	-0.015**	-0.032***
	(0.005)	(0.006)	(0.006)	(0.009)
Wealth (in $10,000)	0.003***		0.004***	0.003***
	(0.001)		(0.001)	(0.001)
CES-D score	0.014	0.016	0.015	0.012
	(0.011)	(0.011)	(0.011)	(0.016)
Poor health	0.110**	0.079*	0.069	0.167**
	(0.045)	(0.047)	(0.050)	(0.079)
Good health	0.016	0.044	0.070	-0.088
	(0.041)	(0.043)	(0.043)	(0.061)
Any ADL limitations	0.008	0.019	0.002	0.046
	(0.049)	(0.050)	(0.051)	(0.085)
Any IADL limitations	0.040	-0.012	-0.020	-0.011
	(0.041)	(0.042)	(0.042)	(0.066)
Years of education	0.023***			0.066***
	(0.008)			(0.015)
Constant	47.29***	44.63***	41.70***	108.3***
	(11.58)	(11.72)	(11.88)	(18.12)
Number of observations (households)	1995(646)	1995(646)	1995(646)	1941(645)
p-value Wald test: all health variables	0.015	0.320	0.214	0.017

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The *p*-value of the Wald test for health indicators indicates that the coefficients of health variables are jointly significant at a 5 percent level of significance. Specifically, being in poor health significantly increases the total consumption relative to annuity income, which is probably because total consumption includes health expenditures. The results under the fourth column in Table 4.7 show that the logarithm of total health expenditures is significantly higher for those who are in poor health. Once we exclude health expenditures from total expenditures (under column 3), the difference between total consumption and annuity income becomes independent of individuals' health status.[38] The results under the fourth column also suggest the logarithm of total health expenditures becomes higher as the level of education increases. At first glance, this finding may seem unexpected because high educated are usually healthier than low educated and, therefore, we expect that they have less spending on health. However, in the United States low-income individuals (who are also low educated) are covered by a social health care program called Medicaid whereas high-income individuals have out-of-pocket expenditures.

Table 4.8 shows the estimation results by the Ordinary Least Squares (OLS) for couple households. Similar to findings for single households, the level of wealth is positively associated with the difference between total consumption and annuity income, suggesting that couple households with more assets tend to spend more than their household annuity income. The age effect in this model is not as strong as in the singles model.

Neither the age of husband nor the age of wife has a significant effect on the difference between total consumption and annuity income.[39] One explanation can be that couple households are usually younger than single households, and therefore, they may have a flatter consumption profile. The *p*-value of the Wald test for health indicators shows that the coefficients of health variables are not jointly significant. On the other hand, the difference between total consumption and annuity income decreases for households in which the wife has any difficulty in instrumental activities of daily living such as handling money, shopping for groceries preparing meals etc. This finding is in line with the predictions of a model proposed by Boersch-Supan and Stahl (1991). In their model individuals' marginal utility of consumption is affected by their health status and, therefore, individuals become consumption constrained due to deteriorating health in old age.

[38] The Wald test (not reported in Table 4.7) for the equality of coefficient estimates on poor health in models (1) and (3) suggests that the estimated coefficient on poor health in model (1) is statistically different than that in model (3).

[39] We also tried to estimate the models in Table 4.8 by controlling for only the age of husband or only the age of wife. In both cases, we did not find a significant age effect.

Table 4.8: Estimation results based on the OLS (two-person households)

	(1) Log total consumption minus log annuity income	(2) Log total consumption minus log annuity income	(3) Log total consumption (excluding health exp.) minus log annuity income	(4) Log total health expenditures
Year of birth_husband	0.001	0.014	0.030	-0.057
	(0.030)	(0.036)	(0.036)	(0.050)
Year of birth_wife	-0.016	-0.028	-0.055*	0.038
	(0.030)	(0.036)	(0.028)	(0.051)
Age_husband	-0.001	0.013	0.028	-0.056
	(0.030)	(0.037)	(0.036)	(0.050)
Age_wife	-0.010	-0.024	-0.053*	0.046
	(0.030)	(0.037)	(0.029)	(0.051)
Wealth (in $10,000)	0.004***		0.006***	0.002***
	(0.001)		(0.001)	(0.001)
Cesd score_husband	0.003	0.003	0.006	-0.022
	(0.014)	(0.015)	(0.015)	(0.027)
Cesd score_wife	-0.008	-0.014	-0.015	-0.029
	(0.012)	(0.012)	(0.013)	(0.021)
Any IADL limitations_husband	0.021	-0.013	-0.013	-0.031
	(0.038)	(0.044)	(0.044)	(0.060)
Any IADL limitations_wife	-0.051	-0.116**	-0.106**	-0.049
	(0.043)	(0.046)	(0.047)	(0.072)
Poor health_husband	0.053	0.023	0.0011	0.138**
	(0.047)	(0.051)	(0.052)	(0.067)
Poor health_wife	0.010	-0.006	-0.012	-0.042
	(0.051)	(0.054)	(0.055)	(0.079)
Good health_husband	-0.024	-0.001	0.007	-0.030
	(0.039)	(0.047)	(0.047)	(0.059)
Good health_wife	-0.002	0.051	0.076*	-0.066
	(0.041)	(0.047)	(0.043)	(0.064)
Any ADL limitations_husband	0.115*	0.096	0.089	0.010
	(0.063)	(0.067)	(0.069)	(0.104)
Any ADL limitations_wife	0.072	0.098	0.106	0.027
	(0.064)	(0.068)	(0.069)	(0.085)
Years of education_husband	0.010			0.027**
	(0.008)			(0.013)
Years of education_wife	0.011			0.018
	(0.011)			(0.020)
Constant	29.90**	28.89**	38.45***	43.70**
	(12.73)	(13.57)	(13.77)	(18.45)
Number of observations (households)	1617(524)	1617(524)	1617(524)	1606(524)
p-value Wald test: all health variables	0.342	0.427	0.612	0.351
p-value Wald test: age	0.579	0.528	0.300	0.257

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Next, we investigate the extent to which individuals' subjective mortality risk is associated with the changes in their consumption at older ages. We first estimate the Euler equation as shown in equation (4.5) where the change in consumption is explained by subjective mortality risk of elderly singles. The estimation results are given in Table 4.9.

Table 4.9: Estimation of the Euler Equation by OLS (one-person households)

	(1) Consumption growth (All categories) $\Delta \ln c_{t+1}$	(2) Consumption growth (All categories) $\Delta \ln c_{t+1}$	(3) Consumption growth (Salm (2010, sub-categories) $\Delta \ln c_{t+1}$	(4) Consumption growth (Salm (2010, sub-categories) $\Delta \ln c_{t+1}$
$\ln\left(1-m_{i,t}^{t-1}\right)$	0.119	0.170	0.294	0.343*
	(0.119)	(0.123)	(0.190)	(0.200)
Change in self-rated health	-0.005		-0.005	
	(0.009)		(0.013)	
Change in any ADL	0.027		0.019	
	(0.020)		(0.028)	
Change in any IADL	0.019		-0.022	
	(0.016)		(0.025)	
Change in CES-D	0.003		0.001	
	(0.004)		(0.006)	
Years of education	0.0003	0.001	-0.002	-0.001
	(0.003)	(0.003)	(0.004)	(0.004)
Poor health		0.023		-0.001
		(0.021)		(0.030)
Good health		0.001		-0.001
		(0.017)		(0.023)
Any IADL limitations		0.003		-0.033
		(0.016)		(0.024)
Any ADL limitations		0.015		0.078**
		(0.023)		(0.034)
CES-D score		0.003		0.009
		(0.004)		(0.006)
Constant	-0.020	-0.046	0.006	-0.014
	(0.045)	(0.047)	(0.064)	(0.064)
Number of observations (households)	1306(641)	1323(646)	1306(641)	1323(646)
p-value Wald test: all health variables	0.327	0.501	0.847	0.084

Robust standard errors are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

In all regressions, the dependent variable is the growth rate of real annual consumption expenditures on nondurables. In the first two models we use all categories of nondurables whereas in the last two models we only include seven categories of nondurables as explained in section 4.3.2. We also control for individuals' health status and education level when we estimate the relationship between the consumption growth and subjective mortality risk. Following Salm (2010) we include health indicators in levels (model 2 and model 4). We also run regressions in which we control for the change in individuals' health status. The latter model is theoretically possible once we assume that individuals' marginal utility of consumption is affected by their health status (See, e.g., Boersch-Supan and Stahl 1991).

Note that all variables on the right-hand side in Table 4.9 are measured in year between t and t+1, therefore, they are exogenous in the sense that they are not correlated with the error term in year t+1.[40] According to Table 4.9 in all specifications the coefficient of subjective mortality risk has an expected sign but it is statistically significant at a 10 percent level of significance only in the fourth model. . The size of the estimate shows that an increase in subjective mortality by 1 %-point is associated with a decrease in consumption of nondurables by approximately 0.34 %-points. This finding suggests that the growth rate of consumption expenditures on sub-categories of nondurables is lower for individuals with higher subjective mortality rates in line with the prediction of the life cycle model outlined in Section 4.2.1. On the other hand, the subjective mortality risk does not explain the growth rate of consumption expenditures on all categories of nondurables probably because some of these categories such as home insurance, property tax, rent, electricity, water, heat etc. are not adjusted in response to changes in the mortality risk. The estimated coefficient on the variable $\ln\left(1-m_{i,t}^{t-1}\right)$ in the fourth model corresponds to a parameter of relative risk aversion which is equal to 2.9. This estimate is consistent with the previous estimates in the literature (See, e.g., Skinner 1985 and Palumbo 1999).

The results under the fourth column also suggest that the growth rate of nondurable consumption is higher for the individuals who have any difficulty in activities of daily living such as eating, bathing, walking etc. In other words, these individuals' current expenditures on sub-categories of nondurables are smaller than their future expenditures on the same categories. The reason behind this finding can be that individuals with difficulty

[40] The CAMS survey is matched to most of the information in the previous HRS wave, i.e. CAMS 2001 is matched to the HRS 2000. The consumption growth between 2003 and 2001 is matched to variables from the HRS dataset in 2002.

in daily activities would spend more money on health services and medical supplies and less money on other categories such as food, dining out, vacations and hobbies. The sub-categories of nondurables in model (4) exclude expenditures on health; therefore, we find that the current expenditures on non-health related categories are lower for unhealthy individuals.

Table 4.10 report the results from the estimation of the Euler equation as shown in equation (4.11) where the change in consumption is explained by the couple's adjusted mortality rate, $cm_{t+1}^{t} - \sqrt{2}^{1-\gamma}\left(pm_{t+1}^{t} + pf_{t+1}^{t}\right)$, and a set of control variables including health indicators (in levels or in first differences) and the level of education for the husband and the wife. In the first two models in Table 4.10, in which we use all categories of nondurable spending, the coefficient on the couple's adjusted mortality rate has an expected sign, although it is not statistically significant. In the last two models, we find an unexpected sign for the coefficient on the couple's adjusted mortality rate, yet the estimate is not statically different from zero. The control variables also do not seem to play a role in determining the growth rate of consumption of elderly couples. On the other hand, the possible correlation between the variables of the husband and the variables of the wife might explain the insignificant coefficient estimates.

One of the reasons why the prediction of the life-cycle model outlined in section 4.2.2 does not hold can be that the assumption of the model regarding the same parameter of relative risk aversion for both spouses may not be supported by the empirical evidence.[41] The existing literature shows that women are more risk averse in financial decision-making than are men.[42] The model can be extended by assuming a different coefficient of relative risk aversion for the husband and the wife. Moreover, instead of estimating the risk aversion parameter directly we replace it with a specific value. Although we run some robustness checks by assigning different values (see footnote 41), the complete analysis requires estimating this parameter directly.

[41] The coefficient of risk aversion is set equal to 3 to calculate the couple's adjusted mortality rate. We also tried the values between 1 and 3 but the estimation results did not change substantially.

[42] See Croson and Gneezy (2009) for a review of the literature on this topic.

Table 4.10: Estimation of the Euler Equation by OLS (two-person households)

	(1) Consumption growth (All categories) $\Delta \ln c_{t+1}$	(2) Consumption growth (All categories) $\Delta \ln c_{t+1}$	(3) Consumption growth (Salm (2010, sub-categories) $\Delta \ln c_{t+1}$	(4) Consumption growth (Salm (2010, sub-categories) $\Delta \ln c_{t+1}$
$\ln\left[1-\left(cm_t^{-1}-\sqrt{2}^{1-\gamma}\left(pm_t^{-1}+pf_t^{t-1}\right)\right)\right]$ [a]	0.263	0.267	-0.064	-0.122
	(0.188)	(0.187)	(0.261)	(0.266)
Change in self health_husband	0.011		0.018	
	(0.009)		(0.012)	
Change in self health_wife	0.011		0.009	
	(0.010)		(0.013)	
Change in any ADL_husband	0.023		-0.014	
	(0.031)		(0.036)	
Change in any ADL_wife	0.013		-0.033	
	(0.025)		(0.030)	
Change in any IADL_husband	0.0001		0.034*	
	(0.017)		(0.020)	
Change in any IADL_wife	-0.009		-0.010	
	(0.018)		(0.023)	
Change in CES-D_husband	-0.0004		0.003	
	(0.006)		(0.009)	
Change in CES-D_wife	-0.001		0.002	
	(0.005)		(0.007)	
Years of education_husband	-0.0004	0.001	-0.002	-0.002
	(0.003)	(0.003)	(0.004)	(0.003)
Years of education_wife	-0.001	-0.002	-0.005	-0.006
	(0.004)	(0.004)	(0.006)	(0.006)
Poor health_husband		0.006		0.015
		(0.023)		(0.030)
Poor health_wife		0.002		-0.022
		(0.024)		(0.031)
Good health_husband		-0.026		0.004
		(0.017)		(0.021)
Good health_wife		-0.009		-0.017
		(0.017)		(0.021)
Any IADL limitations _husband		-0.003		0.030
		(0.016)		(0.021)
Any IADL limitations _wife		-0.011		-0.012
		(0.019)		(0.025)
Any ADL limitations _husband		-0.018		-0.042
		(0.028)		(0.036)
Any ADL limitations _wife		0.011		-0.024
		(0.027)		(0.036)
CES-D score_husband		-0.003		-0.005
		(0.007)		(0.009)
CES-D score_wife		-0.001		0.002
		(0.006)		(0.008)
Constant	-0.011	0.017	0.049	0.060
	(0.048)	(0.055)	(0.073)	(0.078)
Number of observations (households)	1004(506)	1061(524)	1004(506)	1061(524)
p-value Wald test: all health variables	0.845	0.921	0.460	0.802

Robust standard errors are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a] The coefficient of risk aversion is set equal to 3 to calculate this variable.

4.4.1 Sensitivity checks

Following Salm (2010), we instrument subjective mortality rate to account for measurement error and focal point responses. Salm (2010) uses the instrumental variables which are indicators for mother's age at death 76 or younger, mother's age at death 77 to 84, mother's age at death 85 or older, father's age at death 72 or younger, father's age at death 73 to 80, and father's age at death 81 or older and the reference categories are mother is still alive and father is still alive, respectively. For elderly singles, we find that father variables do not significantly predict individuals' subjective mortality risk; therefore, we did not use these variables in our estimation. Instead, we instrument subjective mortality rate with life table mortality rate ($m_{0,t}^{t-1}$) and the mother variables. Results are given in Table 4.11.

According to the first stage results under the columns (2) and (4), life table mortality rate is strongly correlated with subjective mortality rate. The null hypothesis of the Hansen's J statistic in Table 4.11 states that overidentifying restrictions are valid. Failing to reject the null hypothesis indicates that the instruments are exogenous in the sense that they are not correlated with the error term of the consumption growth equation for elderly singles. The F statistics in models (2) and (4) are quite high, showing the strength of the relationship between subjective mortality rate and excluded instruments in the first stage regressions. The last row in Table 4.11 reports Wooldridge's (1995) robust score test statistic to determine whether the endogenous right-hand-side variable in the model, which is subjective mortality rate in our case, is in fact exogenous. The p-value of the exogeneity test statistic in Table 4.11 indicates that the exogeneity of the right-hand-side variable cannot be rejected; suggesting that the IV estimation is not needed and we can rely on the OLS results in Table 4.9.

Table 4.12 shows the IV estimation results of the Euler equation for couple households. We instrument the couple's adjusted mortality rate based on subjective mortality risk of the husband and the wife with the couple's adjusted mortality rate obtained from the life table. We do not use parental longevity variables (the mother's and the father's ages at death) as additional instruments because we find that these variables do not significantly predict the couple's adjusted mortality risk. According to the first stage results in Table 4.12, the couple's adjusted mortality risk obtained from the life table is strongly correlated with the same variable calculated using subjective mortality risk of the husband and the wife.

Table 4.11: Instrumental Variable (IV) Estimation of the Euler Equation (one-person households)

	(1) Consumption growth (Salm (2010, sub-categories) IV $\Delta \ln c_{t+1}$	(2) $\ln(1-m_{i,t}^{t-1})$ First Stage	(3) Consumption growth (Salm (2010, sub-categories) IV $\Delta \ln c_{t+1}$	(4) $\ln(1-m_{i,t}^{t-1})$ First Stage
$\ln(1-m_{i,t}^{t-1})$	0.760*		0.873*	
	(0.434)		(0.470)	
Change in self-rated health	-0.005	-0.0003		
	(0.013)	(0.001)		
Change in any ADL	0.030	-0.013***		
	(0.028)	(0.004)		
Change in any IADL	-0.015	0.001		
	(0.023)	(0.003)		
Change in CES-D	0.001	0.0002		
	(0.005)	(0.001)		
Years of education	-0.003	0.001**	-0.002	0.001
	(0.004)	(0.000)	(0.004)	(0.001)
$\ln(1-m_{0,t}^{t-1})$		0.705***		0.659***
		(0.060)		(0.060)
Mother is still alive (ref.)		-		-
Mother's age at death<= 76		-0.020**		-0.017*
		(0.009)		(0.009)
77<=Mother's age at death<=84		-0.009		-0.007
		(0.009)		(0.009)
Mother's age at death>= 85		-0.0005		0.001
		(0.009)		(0.009)
Poor health			0.019	-0.023***
			(0.031)	(0.004)
Good health			-0.007	0.010***
			(0.023)	(0.003)
Any IADL limitations			-0.030	0.002
			(0.023)	(0.003)
Any ADL limitations			0.085**	-0.005
			(0.034)	(0.004)
CES-D score			0.008	0.0003
			(0.007)	(0.001)
Constant	0.050	-0.039***	0.022	-0.031***
	(0.073)	(0.012)	(0.072)	(0.012)
Number of obs.(households)	1290(630)	1290(630)	1307(635)	1307(635)
F test (p-value)		47.296 (0.00)		41.77 (0.00)
Hansen's J test(p-value)		0.795 (0.85)		1.012(0.798)
Test of exogeneity- χ_1^2 *(p-value)*		1.242 (0.265)		1.279(0.257)

Robust standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4.12: Instrumental Variable (IV) Estimation of the Euler Equation (two-person households)

	(1) Consumption growth (All categories) IV $\Delta \ln c_{t+1}$	(2) First Stage	(3) Consumption growth (All categories) IV $\Delta \ln c_{t+1}$	(4) First Stage
$\ln\left[1-\left(cm_t^{t-1}-\sqrt{2}^{1-\gamma}\left(pm_t^{t-1}+pf_t^{t-1}\right)\right)\right]$ [a]	0.427		0.241	
	(0.433)		(0.472)	
Change in self health_husband	0.011	-0.001		
	(0.009)	(0.001)		
Change in self health_wife	0.011	-0.002		
	(0.010)	(0.002)		
Change in any ADL_husband	0.023	0.001		
	(0.030)	(0.004)		
Change in any ADL_wife	0.013	-0.002		
	(0.025)	(0.003)		
Change in any IADL_husband	0.0003	-0.0003		
	(0.017)	(0.002)		
Change in any IADL_wife	-0.009	0.001		
	(0.018)	(0.002)		
Change in CES-D_husband	0.0000	-0.002**		
	(0.006)	(0.001)		
Change in CES-D_wife	-0.001	0.0003		
	(0.005)	(0.001)		
Years of education_husband	-0.001	0.001**	0.001	0.0001
	(0.003)	(0.0004)	(0.003)	(0.0004)
Years of education_wife	-0.001	0.0006	-0.002	0.00001
	(0.004)	(0.0006)	(0.004)	(0.0005)
$\ln\left[1-\left(cm_{0,t}^{t-1}-\sqrt{2}^{1-\gamma}\left(pm_{0,t}^{t-1}+pf_{0,t}^{t-1}\right)\right)\right]$ [a]		0.833***		0.765***
		(0.0739)		(0.068)
Poor health_husband			0.006	-0.010***
			(0.023)	(0.003)
Poor health_wife			0.002	-0.006*
			(0.025)	(0.003)
Good health_husband			-0.026	0.004*
			(0.017)	(0.002)
Good health_wife			-0.009	0.008***
			(0.018)	(0.002)
Any IADL limitations _husband			-0.003	0.001
			(0.016)	(0.002)
Any IADL limitations _wife			-0.011	-0.001
			(0.019)	(0.002)
Any ADL limitations _husband			-0.018	-0.006*
			(0.028)	(0.003)
Any ADL limitations _wife			0.011	-0.002
			(0.027)	(0.004)
CES-D score_husband			-0.003	-0.003***
			(0.007)	(0.001)
CES-D score_wife			-0.001	-0.0004
			(0.005)	(0.0009)
Constant	0.0002	-0.036***	0.016	-0.017**
	(0.059)	(0.008)	(0.059)	(0.008)
Number of observations (households)	1004(506)	1004(506)	1061(524)	1061(524)
Test of exogeneity- χ_1^2 (p-value)		0.159		0.003
		(0.689)		(0.954)

Robust standard errors are in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. [a] The coefficient of risk aversion is set equal to 3 to calculate this variable.

The second stage results in Table 4.12 suggest that the coefficient on the couple's adjusted mortality rate has an expected sign, yet it is not statistically significant. In line with the estimation results in Table 4.10 we find that the prediction of the life-cycle model for elderly couples does not hold even after accounting for measurement error and focal point responses in subjective survival probabilities of the husband and the wife.

4.5 Conclusions

Previous studies find that individuals do not draw down their assets after retirement which is at odds with the predictions of a simple life cycle model without uncertainty. Hurd (1989, 1999) explain saving behavior of elderly singles and couples by adding lifetime uncertainty and bequest motives to the simple life cycle model. In this paper we test the predictions of the models proposed by Hurd (1989, 1999) for elderly Americans. We also extend the theoretical model of Hurd (1999) for couples. For this purpose we use data taken from Health and Retirement Study (HRS) supplemented with the Consumption and Activities Mail Survey (CAMS). More than half of the individuals in our sample spend more than their annuity income after retirement which indicates most individuals have decreasing wealth profiles in old age as predicted by the theory. Moreover, we find that the difference between total consumption and annuity income increases with the level of wealth for both elderly singles and couples. The findings of the singles model also suggest that the growth rate of consumption expenditures on sub-categories of nondurables is lower for individuals with higher subjective mortality rates. On the other hand, the subjective mortality risk does not explain the growth rate of consumption expenditures on all categories of nondurables probably because some of these categories such as home insurance, property tax, rent, electricity, water, heat etc. are not adjusted in response to changes in the mortality risk.

We also find that the growth rate of consumption of elderly couples does not depend on their adjusted mortality risk, contrary to the prediction of the theory. One of the reasons behind this finding can be that the assumption of the model regarding the same coefficient of relative risk aversion for both spouses may not be supported by the empirical evidence since women tend to be more risk averse than men in financial decision-making.

Overall this paper finds some evidence in favor of wealth decumulation by the elderly after retirement. As a future research we can extend the couples model by assuming a different coefficient of relative risk aversion for the husband and the wife. Another extension would be adding additional uncertainty to the model such as uncertainty about

out-of-pocket medical expenses which could be an important factor to explain savings of the elderly.

4.A Derivation of the Euler Equation

4.A.1 Singles model

Derivation of equation (4.3):

$$\max_{c_t, A_t} \sum_{\tau=t}^{L} (1+\rho)^{1-\tau} a_\tau^t u(c_\tau) + \sum_{\tau=t}^{L} (1+\rho)^{-\tau} m_{\tau+1}^t V((1+r)A_\tau), \quad t = 1,\ldots,L$$

$$\text{s.t.} \quad A_t = (1+r)A_{t-1} + y - c_t, \quad t = 1,\ldots,L$$

$$A_t \geq 0, \qquad t = 1,\ldots,L$$

where

A_t = the net worth at the end of period t

y = the non-capital income (in real terms) in period t, consisting only of annuities which are assumed to be constant over time.

ρ = the rate of time preference

r = the real interest rate

c_t = consumption in period t

a_τ^t = the probability that a person lives in period τ given that he/she survives the period t ,and a_t^t =1.

$m_{\tau+1}^t$ = the probability that a person dies at the beginning of $\tau+1$ given that he/she survives the period t.

L = the maximum age after which the person dies with certainty, i.e. $m_{L+1}^L = 1$.

If we ignore the liquidity constraints, the Lagrangean equation of this problem can be written as:

$$\text{L} = \sum_{\tau=t}^{L} (1+\rho)^{1-\tau} a_\tau^t u(c_\tau) + \sum_{\tau=t}^{L} (1+\rho)^{-\tau} m_{\tau+1}^t V((1+r)A_\tau) - \sum_{\tau=t}^{L} \lambda_\tau [A_\tau - (1+r)A_{\tau-1} - y + c_\tau]$$

where λ_τ is the Lagrange multiplier in period τ. By differentiating the Lagrangean equation with respect to c_t, c_{t+1}, and A_t and setting the derivatives equal to zero, we obtain the following first order conditions:

$$\frac{\partial \mathcal{L}}{\partial c_t} = 0, \quad (1+\rho)^{1-t} a_t^t u'(c_t) - \lambda_t = 0 \qquad (4.A.1)$$

$$\frac{\partial \mathcal{L}}{\partial c_{t+1}} = 0, \quad (1+\rho)^{-t} a_{t+1}^t u'(c_{t+1}) - \lambda_{t+1} = 0 \qquad (4.A.2)$$

$$\frac{\partial \mathcal{L}}{\partial A_t} = 0, \quad (1+\rho)^{-t} m_{t+1}^t V'((1+r)A_t)(1+r) - \lambda_t + \lambda_{t+1}(1+r) = 0 \qquad (4.A.3)$$

By combining equations (A1)-(A3), we find the Euler equation as follows:

$$u'(c_t) = \frac{1+r}{1+\rho}\left[\frac{a_{t+1}^t}{a_t^t} u'(c_{t+1}) + \frac{m_{t+1}^t}{a_t^t} V'((1+r)A_t)\right] \qquad (4.A.4)$$

Let the random variable T denote the period at which the person dies. Then $m_{t+1}^t = P(T = t+1 | T > t)$ is called the "instantaneous mortality rate'' and it gives the probability that person dies at the beginning of period $t+1$ given that he/she survives period t, $t = 1,...,L$. The probability that the person lives in period $t+1$ given that he/she survives the period t is equal to

$$a_{t+1}^t = P(T > t+1 | T > t) = 1 - m_{t+1}^t \quad \text{and } a_t^t = 1, \qquad t = 1,...,L$$

Then the equation (4.A.4) can be re-written as:

$$u'(c_t) = \frac{1+r}{1+\rho}\left[(1 - m_{t+1}^t) u'(c_{t+1}) + m_{t+1}^t V'((1+r)A_t)\right] \qquad (4.A.5)$$

4.A.2 Couples model

Derivation of equation (4.9)

$$\max_{c_t, A_t} \sum_{\tau=t}^{L_{\min}} (1+\rho)^{1-\tau} a_\tau^t u\left(\frac{c_\tau}{\sqrt{2}}\right) + \sum_{\tau=t}^{L_m} (1+\rho)^{-\tau} pm_{\tau+1}^t M\left((1+r)A_\tau\right) +$$

$$\sum_{\tau=t}^{L_f} (1+\rho)^{-\tau} pf_{\tau+1}^t F\left((1+r)A_\tau\right) + \sum_{\tau=t}^{L_{\max}} (1+\rho)^{-\tau} h_{\tau+1}^t V\left((1+r)A_\tau\right)$$

$$\text{s.t.} \quad A_t = (1+r)A_{t-1} + y - c_t, \quad t = 1,\ldots,L_{\max}$$

$$A_t \geq 0, \qquad t = 1,\ldots,L_{\max}$$

where

$u\left(\frac{c_\tau}{\sqrt{2}}\right)$ = the couple's utility from consumption divided by an equivalent scale

ρ = the rate of time preference of the couple

A_t = the net worth at the end of period t

r = the real interest rate

a_τ^t = the probability that both spouses will be alive in period τ given that they survive the period t, and $a_t^t = 1$.

$L_{\min}$ = the lifespan of the couple after which one of the spouses dies with certainty

$pm_{\tau+1}^t$ = the probability that the husband becomes a widower at the beginning of $\tau+1$

L_m = the maximum lifespan of the husband

$pf_{\tau+1}^t$ = the probability that the wife becomes a widow at the beginning of $\tau+1$

L_f = the maximum life span of the wife

$M\left((1+r)A_\tau\right)$ = widower's utility of wealth= $\sum_{\tau=t+1}^{L_m} (1+\rho)^{t+1-\tau} a_\tau^{m,t+1} u(c_\tau)$

$F\left((1+r)A_\tau\right)$ = widow's utility of wealth= $\sum_{\tau=t+1}^{L_f} (1+\rho)^{t+1-\tau} a_\tau^{f,t+1} u(c_\tau)$

$h_{\tau+1}^t$ = the probability that both spouses die at the beginning of $\tau+1$, $V(.)$ is the utility from leaving bequests to the children or others

$L_{\max}$ = the maximum lifespan of the surviving spouse

In case of no bequest motive to the children or others and no liquidity constraints, we can write the Lagrangean equation of this problem as follows:

$$\mathcal{L} = \sum_{\tau=t}^{L_{\min}} (1+\rho)^{1-\tau} a_\tau^t u\left(\frac{c_\tau}{\sqrt{2}}\right) + \sum_{\tau=t}^{L_m} (1+\rho)^{-\tau} pm_{\tau+1}^t \left[\sum_{\tau=t+1}^{L_m} (1+\rho)^{t+1-\tau} a_\tau^{m,t+1} u(c_\tau)\right]$$

$$+\sum_{\tau=t}^{L_f} (1+\rho)^{-\tau} pf_{\tau+1}^t \left[\sum_{\tau=t+1}^{L_f} (1+\rho)^{t+1-\tau} a_\tau^{f,t+1} u(c_\tau)\right] - \sum_{\tau=t}^{L_{\max}} \lambda_\tau \left[A_\tau - (1+r)A_{\tau-1} - y + c_\tau\right]$$

where λ_τ is the Lagrange multiplier in period τ. The first order conditions of this problem are:

$$\frac{\partial \mathcal{L}}{\partial c_t} = 0, \quad (1+\rho)^{1-t} a_t^t \frac{1}{\sqrt{2}} u'\left(\frac{c_t}{\sqrt{2}}\right) - \lambda_t = 0 \tag{4.A.6}$$

$$\frac{\partial \mathcal{L}}{\partial c_{t+1}} = 0, \quad (1+\rho)^{-t} a_{t+1}^t \frac{1}{\sqrt{2}} u'\left(\frac{c_{t+1}}{\sqrt{2}}\right) + (1+\rho)^{-t} pm_{t+1}^t u'(c_{t+1})$$

$$+(1+\rho)^{-t} pf_{t+1}^t u'(c_{t+1}) - \lambda_{t+1} = 0 \tag{4.A.7}$$

$$\frac{\partial \mathcal{L}}{\partial A_t} = 0, \quad -\lambda_t + \lambda_{t+1}(1+r) = 0 \tag{4.A.8}$$

By combining equations (4.A.6)-(4.A.8), we find the following Euler equation:

$$u'\left(\frac{c_t}{\sqrt{2}}\right) = \left(\frac{1+r}{1+\rho}\right)\left[\frac{a_{t+1}^t}{a_t^t} u'\left(\frac{c_{t+1}}{\sqrt{2}}\right) + \sqrt{2}\,\frac{pm_{t+1}^t + pf_{t+1}^t}{a_t^t} u'(c_{t+1})\right] \tag{4.A.9}$$

where $a_t^t = 1$, a_{t+1}^t is the probability that both spouses will be alive in period $t+1$ given that they survive the period t and it is equal to one minus the probability that one of the spouses dies at the beginning of period $t+1$ given that both spouses were alive in period t ($a_{t+1}^t = 1 - m_{t+1}^t$). pm_{t+1}^t is the probability that the husband becomes a widower at the beginning of $t+1$ and pf_{t+1}^t is the probability that the wife becomes a widow at the beginning of $t+1$. Then the equation (4.A.9) can be re-written as:

$$u'\left(\frac{c_t}{\sqrt{2}}\right) = \left(\frac{1+r}{1+\rho}\right)\left[\left(1 - cm_{t+1}^t\right) u'\left(\frac{c_{t+1}}{\sqrt{2}}\right) + \sqrt{2}\left(pm_{t+1}^t + pf_{t+1}^t\right) u'(c_{t+1})\right] \tag{4.A.10}$$

Chapter 5
The Retirement-Consumption Puzzle and Unretirement

5.1 Introduction

According to the standard life cycle theory of consumption with quadratic preferences, anticipated income changes do not affect individuals' consumption profiles because rational agents smooth their consumption over the life cycle using their savings. For example, if retirement is associated with an anticipated decline in income, in the certainty-equivalence model proposed by Browning and Lusardi (1996), the optimal response of individuals is to save before retirement to avoid a consumption decline during retirement.[43] As a result, individuals' level of consumption should not change at retirement. Banks *et al.* (1998) extend the certainty-equivalence model by allowing for non-quadratic preferences and possible nonseparabilities between leisure and consumption and they find that marginal utility of consumption is not smoothed around retirement when individuals retire expectedly. This empirical observation contradicts with the predictions of a life cycle model of consumption and is referred to in the literature as the "retirement-consumption puzzle".

Looking at consumption change at retirement might help to understand whether individuals have saved enough for their retirement. This is of interest from a policy perspective as in many industrialized countries, like in the United States; the social security budget is under strain due to population aging. Therefore, the governments of the industrialized countries adopt some pension reforms to alleviate the problem of aging population. These reforms include reductions in public pensions which require individuals to save more for their retirement. If individuals are forced to reduce their spending at retirement, this may suggest that they have not saved enough for retirement. In this case the reforms aiming to reduce public pensions might be ill-advised.

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[43] The certainty-equivalence model proposed by Browning and Lusardi (1996) predicts that anticipated changes in income have no impact on the level consumption. The assumptions of this model are that agents have intertemporally additive utility functions, capital markets are perfect, preferences are quadratic, agents have rational expectations, and rate of time preference is equal to real interest rate.

Earlier research in this field maintains the assumption that retirement is an “absorbing state” which means that re-entering the labor force after being retired is not possible. As a result, they compare preretirement consumption with post retirement consumption, assuming that retirement is a one-time event. In this paper I relax this assumption and investigate consumption behavior of retirees also after they re-enter the labor force.

Unretirement is defined as returning to the labor force after retirement and has become more popular in some countries in recent decades. (Maestas, 2010; Petersson, 2011; Kanabar 2012). For example, Maestas (2010) shows that at least 26 percent of Americans re-enter the labor force following a retirement spell. Focusing on consumption drop at retirement only may be misleading while unretirement among retirees is so prevalent. For example, those who retired earlier than expected due to unemployment may experience a negative income shock at retirement and therefore may choose to re-enter the labor force to finance their consumption during unretirement. This paper re-addresses the retirement-consumption puzzle by taking into account that individuals may re-enter the labor force after being retired. For this purpose I use nine waves of the Health and Retirement Study (HRS) which represents the population of Americans over age 50 and their spouses.

When looking at the retirement-consumption puzzle, it is important to distinguish whether individuals have retired expectedly or unexpectedly because a consumption drop at retirement when retirement occurred as a result of an unexpected shock does not contradict with the predictions of the life cycle theory of consumption. For example, the study by Smith (2006) finds that British workers reduce their consumption when retirement is involuntary as a result of a health shock or redundancy, whereas they do not change their consumption when retirement is voluntary.[44] In this paper, I use respondents’ subjective retirement expectations as an instrument to distinguish between expected and unexpected retirements. The HRS survey contains a question about individuals’ self-reported probability of working after age 65. I use this probability to test whether consumption changes at expected labor market exits.

The life cycle theory also predicts that consumption does not change with unretirement if individuals’ unretirement occurs as planned. Maestas (2010) finds that the majority of the HRS respondents who unretire planned this transition before retirement. She shows that unretirement is an anticipated event for the HRS respondents and it is not a result of

[44] Smith (2006) defines individuals as voluntary retirees if they retired directly from working and as involuntary retirees if they were observed as unemployed or long-term sick/disabled before they retired.

financial shocks or insufficient savings. In this paper I also estimate a model of unretirement to investigate the characteristics of the respondents who reentered the labor force after being retired. I find that individuals' expectations about working during retirement in the baseline year of the survey strongly predict their future transitions to unretirement. Then I use these expectations as an instrument to distinguish between expected and unexpected unretirements.

This paper is closely linked to Haider and Stephens (2007) in the sense that it looks at consumption change at retirement. Haider and Stephens (2007) investigate retirement-consumption puzzle using questions about retirement expectations in the HRS and the Retirement History Survey (RHS). [45] They instrument individuals' current retirement status with their planned year of retirement and find that, for the RHS sample, the household food consumption drops by 7 percent to 11 percent for male workers who retired as expected. On the other hand, using the first three waves of the HRS survey, they find that retirement is not associated with a significant consumption decline. This paper is different than their study in two ways. First, in contrast with their study, I also take into account the fact that individuals may go back to work after retirement and I examine whether consumption responds to unretirement. Second, Haider and Stephens (2007) focus on male-headed households only and they do not control for the labor market status of the spouse for couple households. Household consumption of couples might be sensitive to the changes in the labor market status of both the head and the spouse. For instance, household consumption may not drop substantially with the head's retirement if his spouse is still working. In this paper I analyze the changes in household consumption with both males' and females' retirement and unretirement. This method also allows me to incorporate single females into the analysis who are often left out in the previous studies (See, e.g., Banks *et al.* 1998, Smith 2006).

The main findings of this paper are as follows: The unretirement decision is mainly determined by pre-retirement expectations of work and financial factors such as the amount of individuals' accumulated savings at the time of retirement and having an occupational pension plan. In contrast with the earlier studies in the literature, this paper does not find a

[45] The HRS and the RHS surveys are both longitudinal and interview older Americans. The RHS was conducted from 1969 to 1979 and included men and unmarried women born between 1905 and 1911. The HRS is an ongoing survey and began in 1992. The initial HRS sample includes respondents who were born between 1931 and 1941 and their spouses (irrespective of their age).

significant drop in food consumption at retirement when retirement is fully anticipated.[46] I also find that men's observed retirement is not associated with a significant drop in food consumption, yet household food consumption decreases by about 7 percent when women become retired expectedly or unexpectedly. The drop in consumption with women's retirement does not necessarily contradict with the prediction of the life-cycle model since in this model one cannot distinguish whether retirement was anticipated or unanticipated. Moreover, a significant drop in household food consumption at the women's retirement can be explained by women's contribution to home production. Household food spending may decrease during women's retirement since women spend more time on meal preparation and shopping than men. Another finding of this paper is that in line with the predictions of the life-cycle model consumption does not respond to unretirement if it is fully anticipated. One of the reasons for this finding could be that post-retirement jobs pay much less than pre-retirement jobs and therefore individuals' income does not increase significantly when they unretire. Overall, the findings of this paper suggest that individuals are able to smooth their consumption around retirement.

The paper is structured as follows: Section 5.2 describes the data and the descriptive statistics. Section 5.3 presents the estimation results for a model of unretirement. Section 5.4 outlines the consumption model and the methods for its estimation. Section 5.5 presents the main estimation results as well as the robustness checks, and Section 5.6 offers some concluding remarks.

5.2 Data

I use nine waves of the HRS survey for the period 1992-2010.[47] The sample consists of the original HRS cohort who were born between 1931 and 1941 and their spouses (irrespective of their age). The HRS is a biennial panel survey of Americans and its respondents were first interviewed in 1992 (Juster and Suzman, 1995). The HRS is well-suited for the purpose of this study since it is a large sample of elderly population and it includes detailed information on employment status, food spending, individuals' expectations of work

[46] Although there is a distinction between consumption and spending, I use them interchangeably throughout the analysis. For nondurable goods consumption is usually the same as spending because consumption and spending occur almost at the same time.

[47] Questions about food spending were not asked in the year 1998. The data is drawn from the RAND HRS database which is a cleaned and user-friendly version of the HRS raw files. Variables that are not available in the RAND dataset were taken from the RAND-Enhanced Fat Files.

during retirement, subjective retirement expectations, health, wealth, and marital status of the respondents.

I select individuals from the initial HRS cohort that entered in 1992 because the question about individuals' expectations of work during retirement was not asked to the other cohorts that entered in the subsequent waves.[48] The HRS survey in 1992 covers about 7,700 households with at least one member aged between 51 and 61. For the analysis I exclude 222 households in which the respondent married or remarried during the observation period 1992-2010. The reason behind this restriction is that the question about the respondent and his/her spouse's expectations of work during retirement was only asked in 1992. I use these baseline expectations to predict the respondent and his/her spouse's future unretirement transitions. If the respondent was single in 1992 and was observed as a couple in the subsequent waves, he/she will not be in the sample because his/her wife expectations of work are not available in the subsequent waves. If the respondent remarried during the observation period, the baseline expectation of his/her spouse in 1992 is not relevant to the unretirement decision of his/her current spouse. Next I restrict the sample to 7,351 households with positive household income in 1992.[49] Household income is before-taxes and it consists of the respondent's income plus his spouse's income for couples. The components of the household income are wage/salary income, capital income, unemployment and disability benefits, social security income, pensions and annuities, income from veteran benefits, welfare and food stamps, alimony, other income, and lump sums from insurance, pension, and inheritance. 7,286 households also have non-missing information on household food spending in 1992. I further restrict the sample to 7,049 households in which the respondent and, if present, his/her spouse have non-missing information on their labor market status. Next I focus on 3,450 households in which the respondent and, if present, his/her spouse were working full time or part-time in 1992. This restriction is imposed because working respondents and their spouses (a) can potentially become retired during the survey period 1992-2010, and (b) are eligible to answer the question on subjective probability of working after age 65 and expectation of work during

[48] The RAND HRS data consists of five cohorts: Initial HRS cohort who was born between 1931 and 1941 was first interviewed in 1992. AHEAD cohort born before 1924 was first interviewed in 1993. Children of Depression (CODA) cohort, born 1924 to 1930, War Baby (WB) cohort, born 1942 to 1947, and Early Baby Boomer (EBB) cohort, born 1948 to 1953, were first interviewed in 1998, 1998 and, 2004, respectively.

[49] At this stage I lose 127 households (1.7 percent) because the household income is equal to zero for these households. The main reason why the household income is equal to zero is that both the head of the household and the spouse (if present) were not working in 1992.

retirement.[50] Among 3,450 households in which the respondent and, if present, his/her spouse were working full time or part-time in 1992, 2,933 of them also have non-missing information on the question about the respondent's and his/her spouse's expectations of work during retirement. 2,865 households also have non-missing information on the question about the respondent's and his/her spouse's probability of working after age 65. The final sample includes 2,461 households which are also observed in at least two consecutive waves.

I use the labor force status information of the respondents and their spouses to define retirement and unretirement. Labor force status measure in the RAND HRS data files classifies respondents and their spouses at each wave as working full-time, working part-time, unemployed, partially retired, fully retired, disabled, or not in the labor force. RAND derives this measure by combining objective and subjective information available in each wave. Working full-time is defined as working 35+ hours per week, and 36+ weeks per year, and working part-time is defined as working less than 35 hours per week or less than 36 weeks per year. Respondents and their spouses are classified as fully retired if they are not working for pay and describe themselves as retired and they are defined as partially retired if they are working part-time and describe themselves as retired. The difference between partially retired and part-time working is that there is mention of retirement in the case of being partially retired. In addition to these definitions and following earlier studies such as Maestas (2010) and Hurd and Rohwedder (2008), I also define individuals who are unemployed, disabled, or not in the labor force as fully retired.

I treat individuals as working if they are working either part-time or full-time, and as retired if they are fully or partially retired. Following Maestas (2010), individuals are defined as unretired if they transitioned from full retirement to full-time/part-time employment or partial retirement or if they transitioned from partial retirement to full-time or part-time employment. The fact that unretirement transitions are identified based on a wave-to-wave changes may lead to understating the importance of unretirement since this method ignores short unretirement spells that may occur between waves. Maestas (2010)

[50] In other words, non-working respondents are excluded as they cannot retire and do not answer the question on subjective probability of working after age 65 and expectation of work during retirement. This exclusion also concerns couple households in which the husband was working but the wife was out of the labor force in 1992. I find that in couple households in which the husband was working in 1992, 65 percent of the wives was also working. Although the sample selection may seem restrictive, I still include 65 percent of the wives due to high rates of female labor force participation in the HRS sample.

uses the detailed job history information to identify short unretirement spells between waves and she finds that only 5 percent of the retirees reenter and exit the labor force between waves. Moreover, she points out that these individuals have a very short duration of unretirement and their annual earnings do not change substantially due to unretirement. In the face of Maestas (2010) evidence, I do not include between-wave unretirement spells in the analysis.

Retirement expectations are measured with a question about subjective probability of working past 65.[51] This question is asked in each wave if the respondent and his/her spouse are younger than age 65 and working. The exact wording of the question is as follows:

"On the same scale from 0 to 100 where 0 means absolutely no chance and 100 means absolutely certain… (Thinking about work in general and not just your present job,) what do you think the chances are that you will be working full-time after you reach age 65?"

I use individuals' retirement expectations available in the last year of their employment (one wave before retirement) to instrument their retirement transition in the next period. For those who did not transition to retirement during the observation period, I use their retirement expectations in the current period.

In this paper, I also investigate the characteristics of the respondents who reentered the labor force after being retired. For this analysis I use only the 2,541 individuals who were observed as retired (fully or partially) in the previous period (in wave t-1) and provided non-missing information on the variables used in the analysis. Then I explain the probability of becoming unretired in the current period (in wave t) using the information from the time of retirement (in wave t-1) and last employment (before wave t-1). The main variable of interest in this analysis is individuals' self-reported expectations of work during retirement. At the baseline year, 1992, the HRS asked survey participants the following question about their plans of work during retirement: "Some people want to stop paid work entirely when they retire, while others would like to continue doing some paid work. What about you? "

Survey participants reported either they will stop paid work entirely or they will continue some paid work during retirement. As it is shown in Section 5.3 individuals' expectations about working during retirement in the baseline year of the survey strongly predict their future transitions to unretirement. In the consumption model (section 5.4) I

[51] Note that the HRS survey also asks about the subjective probability of working past 62. I did not use this variable in the analysis since this variable is missing for individuals who are aged 62 and older.

use these expectations as an instrument to distinguish between expected and unexpected unretirements.

The HRS collected information about household food expenditures in all waves except the fourth wave (in 1998). In theory, households' utility is affected not only by food expenditures but also expenditures spent on other nondurable goods consumed by the household. In practice, food expenditures have been used as a proxy for nondurable expenditures by prior researchers (Haider and Stephens, 2007; Smith, 2006). Although it is not a perfect measure, food is also a nondurable good, therefore, changes in food expenditures are closely related to changes in household utility.[52]

Food expenditures are available at the household level and the questions on food expenditures were answered by the financial respondent.[53] These expenditures consist of three separate categories: food at the store, food delivered to the door, and food eating out (See Appendix 5.A for the exact wording of these questions). For the households who are receiving government food stamps last month, the survey asks about the quantity of food stamps received and the additional amount of money spent on these three categories. For those who are not receiving food stamps, the survey asks about expenditures on the same categories. Based on these questions I calculate total annual food expenditures for each household.

5.2.1 Descriptive Statistics

The sample which is used in the consumption regressions includes 2,461 households as introduced in Section 5.2. Among these households 1,343 were couples and 1,118 were singles in 1992, for a total of 3,804 working individuals.[54] Among these individuals 2,323 of them have become retired during the observation period 1992-2010 (61.07 percent). 735

[52] In 2001, the CAMS, a supplemental survey to the HRS, began to collect data on households' total spending including nondurable expenditures. However, this survey was interviewed a subsample of original HRS respondents, therefore it contains smaller number of observations. In this subsample there are a few individuals who re-entered the labor force after retirement. Section 5.5 reports some descriptive statistics and estimation results based on this subsample as well.

[53] In couple households, household level questions about finances are answered by one individual called the 'financial respondent'. In single households, the only respondent is the financial respondent.

[54] In couple households the respondent and his/her spouse are married or have a partnership. In single households the respondent is single, never married, divorced, separated or widowed. In single households and couple households, the household size can be greater than one and two, respectively, because these households can live with their children or parents.

individuals have re-entered the labor force after a retirement spell (31.64 percent). Among these unretirees 434 of them re-entered the labor force two years after retirement, which is the next wave following retirement (59.05 percent). This finding may suggest that the majority of the individuals who go back to work do so within a short period following retirement. Maestas (2010) finds that 26 percent of the retirees in the HRS survey reverse their retirement decision during the observation period from 1992-2002. The unretirement rate in this study, which is about 32 percent, is higher compared to the unretirement rate in Maestas (2010) probably because I use four additional waves of the HRS survey which allows me to observe more transitions to unretirement.

Table 5.1 illustrates median total food spending and income around the time of retirement and unretirement of men and women in couple households. Similar statistics for single households are reported in Table 5.2. The median food spending is reported for two different groups. The first group consists of retirees who became retired in wave zero and stayed retired in the next wave (in wave one). The second group includes unretirees who became unretired in wave zero and also observed as unretired in the next wave. Household food expenditures and income are divided by the OECD-modified equivalence scale.[55] Both food spending and income are measured in 2004 dollars.

According to Table 5.1, for couples, the husband's and the wife's retirements are associated with a drop in household income which is about 19 percent and 18 percent, respectively. On the other hand, household total food spending falls with the husband's retirement by 5 percent whereas it falls with wife's retirement by 9 percent. A smaller drop in household consumption compared to that in household income may suggest that couples have enough savings to smooth their food consumption around retirement. Women's contribution to home production might explain a larger drop in household food spending with the wife's retirement. Women may spend more time on home production and shopping than men during retirement which reduces expenditures on food eating out and bought at the store. Using a cross section sample of American households from the CAMS survey Hurd and Rohwedder (2005) find that, 60-64 year-old retired men and women spent 1.3 and 2.8 hours more on shopping and meal preparation than men and women who were not retired, respectively.

[55] See Hagenaars *et al.*(1994) for the details of the OECD-modified equivalence scale. Household income is the sum of the respondent's income and the spouse's income (if present) and does not include the income of the other members of the household. Therefore, household income of the couples is divided by 1.5.

Table 5.1: Median real annual spending on food and income (in 2004 dollars), couples

	Household Income						**Household Food spending**					
	Males						Males					
	Retirement in wave 0			Unretirement in wave 0			Retirement in wave 0			Unretirement in wave 0		
waves	No. Obs	Median	% change	No. Obs	Median	% change	No. Obs	Median	% change	No. Obs	Median	% change
-1	853	51202		271	39920		853	3993		271	3756	
0	853	41539	-19	271	36091	-10	853	3803	-5	271	3650	-3
1	551	32013	-23	123	37353	3	551	3756	-1	123	3565	-2
	Females						Females					
	Retirement in wave 0			Unretirement in wave 0			Retirement in wave 0			Unretirement in wave 0		
waves	No. Obs	Median	% change	No. Obs	Median	% change	No. Obs	Median	% change	No. Obs	Median	% change
-1	780	48886		230	38106		780	4159		230	3808	
0	780	40214	-18	230	39318	3	780	3803	-9	230	3899	2
1	578	33453	-17	113	36000	-8	578	3640	-4	113	3803	-2

Table 5.1 also shows that household income is 10 percent lower when the husband becomes unretired whereas the wife's unretirement is associated with an increase in income which is about 3 percent. Although individuals start to earn wage income when they unretire, it seems that their wage income does not exceed their retirement income substantially. In the United States, when individuals return to work after retirement, they may no longer receive employer pensions if they return to their former employer. For example, an individual may retire before the legal retirement age, which is 65 for those born before 1943 and between 66 and 67 for people born in 1943 and later, and may start receiving employer pension benefits. If this person decides to return to his/her former employer, he/she may have to give up pension benefits because it is not legal to be an employee and a pensioner of the same firm before the legal retirement age (Maestas 2010). If this is the case, it is expected that individuals' unretirement income is lower than their retirement income. It is also likely that individuals may prefer to suspend their social security benefits after they become unretired. In the United States, individuals may stop benefits within 12 months of first claiming by repaying the benefits received during the last 12 months. They may also suspend their benefits after reaching the legal retirement age and delay receiving them until the age 70. This is an appealing option since each year of delay corresponds to 5 percent to 8 percent (depending on the year of birth) increase in

retirement benefits.[56] Moreover, Maestas (2010) finds that the median wage earned on unretirement jobs are significantly lower than that on pre-retirement jobs which may also be reason that unretirement is not associated with a significant increase in the household income. Table 5.1 also reveals that household food consumption is slightly lower when the husband becomes unretired whereas the wife's unretirement is associated with a 2 percent increase in household food spending. The finding that household consumption does not increase substantially with unretirement is expected given that unretirement does not lead to a significant increase in household income. On the other hand, a small increase in food consumption with the wife's unretirement can be explained by the wife's contribution to home production. When the wife becomes unretired home production may drop which may cause household food expenditures to go up again.

According to Table 5.2, single men's income drops by 30 percent with retirement, whereas single women experience a fall in income at the time of retirement which is about 27 percent. On the other hand, single men's retirement does not reduce household food spending at all while single women's retirement is associated with a decrease in household food spending by 9 percent. One reason behind this finding can be that single women do not have sufficient amount of savings to smooth consumption at retirement compared to single men, since women earn less money than men over the life cycle (see Table 5.B.1 in section 5.B). Another reason can be that single women's contribution to home production may be higher than that of single men which reduces expenditures on eating out. Table 5.2 also suggests that, income is slightly higher when single men or women become unretired. Regardless of gender, single households do not start consuming more in the first year of their unretirement (in wave 0) whereas single men's income and consumption is higher in the third year of their unretirement (in wave 1) than in their last period of retirement (in wave -1).

Table 5.3 shows the changes in sub-categories of household food spending around the time of retirement and unretirement of men and women in couple households. Retirement may reduce expenditures on food eating out because retirees may spend more time on meal preparation than workers.

[56] http://m.kiplinger.com/article/retirement/T037-C000-S004-paycheck-impact-on-retirement-income-benefits.html

Table 5.2: Median real annual spending on food and income (in 2004 dollars), singles

	Household Income						Household Food spending					
	Males						Males					
	Retirement in wave 0			Unretirement in wave 0			Retirement in wave 0			Unretirement in wave 0		
waves	No. Obs	Median	% change	No. Obs	Median	% change	No. Obs	Median	% change	No. Obs	Median	% change
-1	163	42379		45	28985		163	3641		45	3276	
0	163	29472	-30	45	29179	1	163	3650	0	45	2817	-14
1	104	24062	-18	21	33891	16	104	3433	-6	21	3411	21
	Females						Females					
	Retirement in wave 0			Unretirement in wave 0			Retirement in wave 0			Unretirement in wave 0		
waves	No. Obs	Median	% change	No. Obs	Median	% change	No. Obs	Median	% change	No. Obs	Median	% change
-1	527	28378		189	21332		527	3130		189	2889	
0	527	20783	-27	189	21618	1	527	2852	-9	189	2852	-1
1	363	16648	-20	78	26340	22	363	2680	-6	78	2827	-1

Table 5.3: Median real annual spending on food (sub-categories) (in 2004 dollars), couples

	Food at home				Food at home			
	Men				Women			
waves	Retired in wave 0	% change	Unretired in wave 0	% change	Retired in wave 0	% change	Unretired in wave 0	% change
-1	3042		2730		2981		2881	
0	2817	-7	2730	0	2852	-4	2889	0
1	2730	-3	2535	-7	2707	-5	2730	-5
	Food eating out				Food eating out			
	Men				Women			
waves	Retired in wave 0	% change	Unretired in wave 0	% change	Retired in wave 0	% change	Unretired in wave 0	% change
-1	921		815		949		911	
0	884	-4	901	11	910	-4	932	2
1	912	3	912	1	867	-5	974	5

Notes: Food at home includes food at the store and food delivered to the door. The underlying number of observations is the same as in Table 5.1.

According to Table 5.3, median household spending on eating out falls with both the husband's and the wife's retirement. Similarly, both the wife's and the husband's unretirement are associated with an increase in the median spending on eating out. Table 5.3 also shows that the median spending on food at home drops with both the husband's and the wife's retirement. The increased leisure time in retirement may lead to more efficient shopping which may reduce expenditures on food bought at the store.

According to Table 5.4, median spending on eating out is slightly lower when single men become retired whereas it decreases by 16 percent when single women become retired. Single women's expenditures on food at home also fall with retirement by 6 percent while single men's expenditures in the same category are higher at the time of retirement. On the other hand, both single men and women do not start spending more on eating out in the first year of unretirement, yet single women's spending on eating out is higher in the third year of unretirement (in wave 1).

Table 5.4: Median real annual spending on food (sub-categories) (in 2004 dollars), singles

	Food at home				Food at home			
	Men				Women			
waves	Retired in wave 0	% change	Unretired in wave 0	% change	Retired in wave 0	% change	Unretired wave 0	% change
-1	2289		2184		2504		2436	
0	2374	4	1997	-9	2366	-6	2281	-6
1	2504	5	2129	7	2194	-7	2281	0
	Food eating out				Food eating out			
	Men				Women			
waves	Retired in wave 0	% change	Unretired in wave 0	% change	Retired in wave 0	% change	Unretired in wave 0	% change
-1	1020		1036		420		385	
0	994	-3	912	-12	353	-16	323	-16
1	897	-10	974	7	255	-28	417	29

Notes: Food at home includes food at the store and food delivered to the door. The underlying number of observations is the same as in Table 5.2.

5.3 Model of Unretirement

In this section, I investigate the characteristics of the HRS respondents who reentered the labor force after being retired. As explained in Section 5.2, these results are based on an unbalanced panel of individuals who were retired in the previous period. I estimate a Probit model where the dependent variable is a dummy which takes one if individuals transitioned to unretirement in period t and 0 otherwise. According to Maestas (2007) in a dynamic retirement model, optimal unretirement could arise through two channels. Firstly, dynamic preferences for leisure would affect individuals' decision to unretire. For example, individuals who work in a stressful job, and feel burned out, would become retired. After having enough time to recover, work may become attractive again. This is called the burnout and the recovery process. Secondly, the arrival of new information after retirement regarding financial situation, or satisfaction with retirement could cause an individual to update his expectations of work during retirement. For example, an unexpected drop in stockholdings due to a stock market decline may increase the probability of unretirement. Similarly, individuals who realized that retirement was not as enjoyable as they expected may go back to work. Following Maestas (2007) I estimate the probability of unretirement on a set of variables. Table 5.5 summarizes the estimation results. The variables with the star (*) are constructed based on information in the last year of employment and the rest of the variables are based on information in period $t-1$.

The first row in Table 5.5 shows that those who reported in the baseline year of the survey that they would continue doing some paid work during retirement are more likely to transition to unretirement in the current period. Although it is a drawback that these expectations are not available in the subsequent waves of the HRS, it is promising that the baseline expectations still strongly predict individuals' future unretirement. The estimated marginal effect at the mean also suggests that an average respondent who planned to work during retirement in 1992 is about 3 % - points more likely to become unretired in the current period compared to an average person who reported that he/she would stop work entirely during retirement. Compared to the average rate of becoming unretired in the current period which is about 10 percent, the size of the marginal effect is considerable.

The second row in Table 5.5 shows that someone's probability of becoming unretired in the current period is higher if he/she reported a higher probability of working full-time after age 65 in the last year of employment.

Table 5.5: Estimation results for the unretirement model
Dependent variable: Probability of becoming unretired in period t

	Probit Estimation	
	Marginal effects[a]	Std.err.
Planned to work during retirement in 1992	0.031***	0.006
Prob. of working after 65*	0.042***	0.010
Managerial/professional specialty*	0.004	0.010
Sales/admin support*	-0.004	0.009
Services*	-0.009	0.010
Precision production/craft/repair*	-0.012	0.012
Operators and laborers*	-	-
Pension plan, Defined Benefit (DB)*	-	-
Pension plan, Defined Contribution (DC)*	0.015*	0.009
Pension plan, DB and DC*	0.014	0.017
No pension plan*	0.035***	0.008
Years in retirement (in period t)	-0.007***	0.001
Income, Quartile[1st]	-0.022**	0.010
Income, Quartile[2nd]	-0.005	0.009
Income, Quartile[3rd]	0.003	0.008
Income, Quartile[4th]	-	-
Consumption, Quartile[1st]	-0.012	0.009
Consumption, Quartile[2nd]	0.001	0.008
Consumption, Quartile[3rd]	0.007	0.008
Consumption, Quartile[4th]	-	-
Wealth, Quartile[1st]	0.028**	0.012
Wealth, Quartile[2nd]	0.017*	0.010
Wealth, Quartile[3rd]	-0.003	0.008
Wealth, Quartile[4th]	-	-
Age	-0.007***	0.001
Couple	-0.017**	0.009
Household size	0.004	0.003
Low education	0.012	0.010
Medium education	-	-
High education	0.005	0.009
Good Health	0.025***	0.007
Fair Health	-	-
Poor Health	-0.035***	0.007
Male	0.018***	0.008
White	-0.024**	0.011
Black	-	-
Other race	0.016	0.021
Number of Observations (Individuals)	7,889 (2,541)	

Notes: [a]Marginal effects are at the mean values. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Year dummies are included Wealth, consumption and income are measured at the household level and in 2004 dollars.

The coefficient on operators and laborers is not statistically different than those on the other occupational groups (i.e. managerial/professional specialty, services, etc.) suggesting that unretirement rates are the same across different occupation groups. Table 5.5 also reveals that those who have a defined benefit (DB) pension plan from the last employment are less likely to reverse their retirement compared to those who have defined contribution (DC) pension plan or no pension plan at all. In the DB pension plan employees receive a fixed annual amount during their retirement and this amount is determined by their age, years of service and salary. In the DC pension plan employees contribute a fixed amount in each year and these contributions are invested, for example, in the stock market. The pension income under the DC plan is determined by the return on the investments which can be positive or negative. Therefore, DC plan holders may face greater uncertainty regarding their retirement benefits compared to DB plan holders. As a result, it is expected that DC plan holders are more likely to unretire to finance their retirement years compared to DB plan holders. Table 5.5 also shows that the coefficient on years since retirement is negative and highly significant suggesting that those who stay longer in retirement are less likely to unretire than those who stay shorter. If individuals realized that retirement was not as enjoyable as they expected, they may return to work shortly after retirement. The fact that an individual's work skills depreciate if he/she stays in retirement longer may also affect both the employer's willingness to hire an old worker and the employee's willingness to work.

Among the financial factors, household wealth at the time of retirement plays a role in the decision of unretirement. Those who are in the lower wealth quartiles (first and second) are more likely to unretire than those who are in the highest wealth quartile. On the other hand, the level of food consumption at the time of retirement does not seem to determine the decision to become unretired in the next period. Table 5.5 also shows that those who live in the low income households are less likely to unretire than those who live in the high income households. The findings also suggest that age is negatively associated with the likelihood of unretirement. Those who live in couple households are less likely to reverse their retirement than those who live in single households. The health status at the time of retirement also plays a key role in the decision of unretirement: The healthier are more likely to reverse their retirement. There is also a gender effect in the decision to unretire such that the probability of unretirement is higher for males than for females. The results regarding race shows that white people are less likely to go back to work after retirement compared to black people. Overall, the findings of this section show that individuals' pre-retirement expectations of work play a key role in the decision of unretirement which may suggest that most of the unretirement transitions are anticipated before retirement. On the other hand, the probability of unretirement is also determined by financial factors such as the amount of individuals' accumulated savings at the time of retirement. This latter finding may imply that for some individuals unretirement was not fully anticipated before retirement. The arrival of new information after retirement regarding financial situation may cause individuals to update their expectations of work during retirement.

5.4 The Consumption Model

Following Smith (2006), I estimate a consumption model derived from Frisch's demand function (Browning et al., 1985). In this model individuals choose consumption (C_t) and leisure (L_t) to maximize the following value function:

$$V(A_t, t) = \max\left\{U(C_t, L_t, \mathbf{X}_t) + \frac{1}{1+\rho}\mathrm{E}_t V(A_{t+1}, t+1)\right\} \tag{5.1}$$

subject to the budget constraint

$$A_{t+1} = (1+r_t)(A_t + B_t + w_t(T - L_t) - C_t) \tag{5.2}$$

where, $\mathbf{X}_t$ is a vector of individual's characteristics, T is the individual's time, ρ is the individual's rate of time preference, A_t is total wealth, r_t is the interest rate, B_t is non-labor income, w_t is the wage rate. This model gives the following first order conditions for the marginal utility of consumption, marginal utility of leisure, and marginal utility of wealth $\lambda_t (= \partial V / \partial A_t)$:

$$U_C(C_t, L_t, \mathbf{X}_t) = \lambda_t \tag{5.3}$$

$$U_L(C_t, L_t, \mathbf{X}_t) = \lambda_t w_t \tag{5.4}$$

$\lambda_t = \dfrac{1+r_t}{1+\rho}\mathrm{E}_t \lambda_{t+1}$, or equivalently

$$\frac{1+r_t}{1+\rho}\frac{\lambda_{t+1}}{\lambda_t} = 1 + \varepsilon_{t+1} \tag{5.5}$$

where ε_{t+1} is a forecast error such that $\mathrm{E}_t \varepsilon_{t+1} = 0$. λ_t contains all information from other periods that is needed to solve the maximization problem in period t. Equation (5.5) describes the rule for the allocation of wealth over time under uncertainty. According to this rule, the individual chooses savings such that the marginal utility of wealth in period t is equal to the discounted expected marginal utility of wealth in period $t+1$. In this model unanticipated shocks will be reflected in the marginal utility of wealth over time.

The log-linearization of equation (5.5) yields:

$$\ln \lambda_t = b_t^* + \ln \lambda_{t-1} + v_t \tag{5.6}$$

where $\mathrm{E}_{t-1}v_t = 0$, $b_t^* = \mathrm{E}_{t-1}\ln(1+\varepsilon_t) - \ln(1+r_t) + \ln(1+\rho)$.

Equation (5.3) implies a Frisch demand function conditional on labor supply[57]:

$$C_t = C(\lambda_t, L_t, \mathbf{X}_t) \tag{5.7}$$

where consumption demand C_t is expressed as a function of individual's current characteristics, leisure, and the marginal utility of wealth which contains all expected future information including the effect of retirement (or unretirement) if it is an anticipated event.

By assuming the within-period utility functions exhibit constant relative risk aversion (CRRA), $U(.)$ can be expressed as:

$$U(C_t, L_t, \mathbf{X}_t) = \frac{\exp(\theta' \mathbf{X}_t + \eta L_t)}{1-\gamma} C_t^{1-\gamma} \tag{5.8}$$

where γ is the coefficient of risk aversion for the household. Using the first order condition for marginal utility of consumption and equation (5.6), one can derive the consumption growth equation as follows:

$$\Delta \ln C_t = \psi b_t^* + \boldsymbol{\beta}' \mathbf{\Delta X}_t + \alpha \Delta L_t + u_t \tag{5.9}$$

where $\psi = -\frac{1}{\gamma}$, $\boldsymbol{\beta}' = \frac{1}{\gamma}\boldsymbol{\theta}'$, $\alpha = \frac{1}{\gamma}\eta$, $u_t = \psi v_t$ and $\mathrm{E}_{t-1}u_t = 0$.

In the empirical implementation of this model I will estimate the following equation:

$$\Delta \ln C_{it} = \boldsymbol{\alpha}' \Delta \mathbf{L}_{it} + \boldsymbol{\beta}' \Delta \mathbf{X}_{it} + u_{it} \tag{5.10}$$

where $i = 1,\ldots,N$ and $t = 1,\ldots,T$, $\Delta \ln C_{it} = \ln C_{it} - \ln C_{it-1}$, $\ln C_{it}$ is the natural logarithm of food expenditures, **L** is vector of dummies indicating the labor market status of the respondent, **X** includes household size, a quadratic specification for age, labor market status of the spouse (if present), and a couple dummy indicating whether the household members are married or have a partnership in period *t* and zero otherwise. The labor market status of the respondent or the spouse at time *t* might be correlated with the forecast error u_t since the model described above assumes that $\mathrm{E}_{t-1}u_t = 0$. In other words, u_t is uncorrelated with the variables in the information set available to the household at time $t-1$, yet labor market status at time *t* is not in the information set available at time $t-1$.

[57] Labor supply is difficult to model because of corner solutions. The conditional demand function in equation (5.7) holds whether or not the hour variable, $T - L_t$, is equal to zero. See the discussion in Browning and Meghir (1991).

For example, individuals may be forced to retire due to unexpected shocks such as unemployment or an adverse health event at time *t*, and as a result they may be forced to reduce their consumption simultaneously. The drop in consumption at time t is not necessarily at odds with the predictions of the life cycle model described above since this effect is a combination of expected and unexpected retirements. Therefore, one needs to distinguish between expected and unexpected retirements (or unretirements). For this purpose, I estimate the parameters in the equation (5.10) with a Generalized Methods of Moments estimator (GMM) introduced by Hansen (1982). This estimation method consists of two stages. In the first stage retirement and unretirement are regressed on a set of instruments that are correlated with retirement and unretirement but that are assumed to be uncorrelated with the error term in equation (5.10). In the second stage, predicted retirement and unretirement are calculated for each individual using the first stage results and these predicted variables are used to replace the endogenous labor market status in equation (5.10). Under the rational expectations hypothesis, i.e. $\mathrm{E}_{t-1}u_t = 0$, all variables measured at time $t-1$ and earlier are exogenous and therefore, they are potential instruments. Following Haider and Stephens (2007), I instrument the respondent's and his/her spouse's retirement status with their expectations about retirement, which are measured with their subjective probabilities of working after age 65 in the last year of employment.[58] Similarly, I use individuals' expectations of work during retirement available in 1992 to instrument their unretirement status in period *t*. Following Banks et al. (1998) I also use individuals' lagged labor market status as additional instruments. If the predictions of the model described above hold, I expect to see no change at retirement or unretirement if these events are fully anticipated, so the estimated coefficients based on GMM estimation should be equal to zero.

5.5 Estimation

5.5.1 Main estimation results

This section presents the estimation results based on a consumption equation described in equation (5.10). In addition to the consumption equation, I also estimate an income equation to see how household income is associated with changes in the labor market status

[58] The instrument in Haider and Stephens (2007) is based on individuals' expected year of retirement which is available in 1992. Although a similar expectation question is asked in the subsequent waves, fewer individuals answered this question which does not allow me to use their most recent expectations. (See Haider and Stephens (2007), footnote 6 for details.)

of the respondent and his/her spouse (if present). I expect that retirement is associated with a decline in income since the replacement rate, defined as the ratio of post-retirement income to pre-retirement income, is less than 100 percent in the United States. I estimate a pooled regression for couple and single households (See section 5.5.2.3 for a separate analysis). Table 5.6 reports the estimation results. According to these results, couple households' income is 58 percent higher than single households' income. Similarly, couples spend 36 percent more on food than singles. Household size is also positively associated with expenditures on food.

The first two columns in Table 5.6 show the results based on the Ordinary Least Squares (OLS) estimation of the consumption and income equations. According to these results, household income falls with men's retirement by about 22 percent whereas women's retirement is associated with a drop in income which is about 16 percent. This finding suggests that women have higher replacement rates than men. The differences between men and women may stem from the fact that men have higher earnings compared to women because they (a) earn higher wages than women and (b) work more years than women (they retire later and/or have less work interruptions). In the United States, the social security benefit formula is designed to provide progressive benefits in the sense that it replaces a larger share of pre-retirement earnings for low earners compared to high earners (Munnell and Soto, 2005). As a result, replacement rates are higher for women than men.

The first column in Table 5.6 shows that household food consumption decreases by about 7 percent when women become retired. On the other hand, men's retirement does not change household food spending significantly. The drop in consumption at observed retirement is not necessarily at odds with the predictions of the life cycle model described above since this effect is a combination of expected and unexpected retirements. The life cycle model only predicts that consumption does not change if retirement occurs as planned. If unexpected shocks such as unemployment or health shocks are correlated with the retirement status at time *t*, consumption may decline around the time of retirement. Therefore, it is important to distinguish between expected and unexpected retirements. Although the OLS estimates in the consumption equation are not consistent due to the possible endogeneity, it is promising that the drop in household consumption is much smaller than the drop in household income suggesting that individuals have enough savings to smooth their consumption around the time of retirement. A larger significant drop in household food consumption at the women's retirement can also be explained by women's contribution to home production during retirement.

Table 5.6: Estimation of household food spending, couples and singles together

	(1) Change in log consumption OLS	(2) Change in log income OLS	(3) Change in log consumption GMM
Change in couple dummy	0.357***	0.576***	0.355***
	(0.042)	(0.067)	(0.043)
Change in household size	0.106***	-0.002	0.107***
	(0.009)	(0.010)	(0.010)
(Men, Age)/10	0.003	0.005**	0.004
	(0.001)	(0.002)	(0.005)
(Women, Age)/10	0.004	0.001	0.005
	(0.003)	(0.005)	(0.005)
Men, become retired	-0.025	-0.220***	-0.018
	(0.018)	(0.024)	(0.108)
Women, become retired	-0.070***	-0.163***	-0.052
	(0.017)	(0.021)	(0.118)
Men, become unretired	0.028	-0.039	-0.129
	(0.034)	(0.053)	(0.274)
Women, become unretired	0.010	0.094**	-0.101
	(0.033)	(0.037)	(0.297)
Constant	-0.037	0.006	-0.048**
	(0.022)	(0.033)	(0.021)
Number of observations (households)	10,587(2,461)	10,587(2,461)	10,587(2,461)
Hansen's J test (p-value)			3.817 (0.431)
Partial F test			
Men, become retired			275.18
Women, become retired			274.61
Men, become unretired			42.37
Women, become unretired			54.85
AP F test for weak identification			
Men, become retired			34.04
Women, become retired			33.88
Men, become unretired			19.97
Women, become unretired			11.86
Test of exogeneity- χ^2_4 *(p-value)*			12.099 (0.016)

Standard errors in parentheses are robust to the presence of heteroscedasticity.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Year dummies are included.

The results regarding unretirement suggest that men's unretirement is not associated with a significant increase in household income whereas women who unretired have a 9 percent higher income. On the other hand, household food consumption does not respond to either men's or women's unretirement. Although in the OLS estimation I cannot distinguish between expected and unexpected unretirements, insignificant coefficient estimates may suggest that individuals smooth their consumption around the time of unretirement. The third column in Table 5.6 presents the results from the GMM estimation. The instruments used in the first stage regressions are, for both men and women, the probabilities of working after age 65 based on the last year of employment, expectations of work during retirement available in 1992, one period lag of working and retired dummies. Note that I interact 1992 expectations of work during retirement with one minus working dummy in *t-1* in order to increase the predictive power of this instrument. Since this instrument is only available in 1992, it is assumed to be constant over time. However, in 1994 the unretirement dummy is zero for each individual in the sample because all respondents and their spouses are working in 1992 so that they may either become retired or continue working in 1994. Using the interaction variable ensures that expectations of work during retirement are irrelevant for those who were working in the previous period.

The null hypothesis of the Hansen's J statistic in Table 5.6 states that overidentifying restrictions are valid. Failing to reject the null hypothesis indicates that the instruments are exogenous in the sense that they are not correlated with the error term in the consumption equation (Equation 5.10). The partial F statistics are quite high which shows the strength of the relationship between the endogenous variables and excluded instruments in the first stage regressions. On the other hand, F statistics from the first stage regressions may not be valid to test the weakness of the instruments if there are multiple endogenous variables in the second stage. Angrist and Pischke (2009, pp. 217-18) propose a method to calculate the F statistics when there are multiple endogenous variables. Table 5.6 reports Angrist and Pischke (AP) F test for weak identification for each of the endogenous regressor. The null hypothesis of the AP F test is that the particular endogenous variable alone is weakly identified. The critical values for the AP F test for weak identification are not available but one can use the "rule of thumb" of Staiger and Stock (1997), which says that if F statistic is at least 10, the weak identification is not a problem anymore. Table 5.6 shows that the AP F test is greater than 10 for each of the endogenous regressor which confirms that the excluded instruments strongly predict the endogenous variables.

The last row in Table 5.6 reports Wooldridge's (1995) robust score test statistic to determine whether the endogenous right-hand-side variables in the model are in fact exogenous. The rejection of the null hypothesis indicates that the variables are endogenous at 5 percent level of significance, which may suggest that the GMM estimation is more reliable than the OLS estimation. According to the GMM estimation results, regardless of gender, household food consumption does not change significantly at the time of retirement or unretirement. This finding is in line with the prediction of the life cycle model described above in the sense that consumption does not change at the time of retirement or unretirement if these events are fully anticipated. In contrast with Banks et al. (1998) and Haider and Stephens (2007), this study does not find a drop in consumption at retirement if retirement is fully anticipated. These aforementioned studies which find a retirement-consumption puzzle use relatively old datasets from the 70s and 80s. The replacement rates for older cohorts might be different than the replacement rates for younger cohorts. The recent study by Smith (2006) which looks at relatively younger cohorts, finds that food spending of British workers does not change significantly when they retire voluntary, but there is a significant drop in food spending when retirement is involuntary. Similarly, Haider and Stephens (2007) find that the HRS respondents do not experience a fall at expected retirement whereas the RHS respondents, who are relatively older than the HRS respondents, reduce their food consumption about 7 percent to 11 percent when they retire expectedly. Overall, the findings of this study are in line with the recent studies which do not find a significant drop in consumption at retirement.

5.5.2 Robustness Checks

5.5.2.1 Nondurable Consumption

Data in this section cover the period from 2001 to 2009 and were taken from the CAMS survey which is a supplemental survey to the HRS. In 2001 the CAMS survey sent questionnaires to a subsample of the households who were interviewed in the HRS 2000 core survey. If household members are married or have a partnership, the questionnaire was sent to one of the spouses, selected randomly. In the initial wave of the CAMS survey 3,866 households answered questions about total nondurable spending based on 26 categories (see Hurd and Rohwedder, 2008 for details). This survey has smaller number of households and covers a shorter time period than the HRS, therefore, I observe fewer retirement and unretirement transitions in this sample than in the HRS sample. The CAMS survey is matched to the most of the information in the previous HRS wave, i.e. CAMS 2001 is matched to the HRS 2000. However, information on financial variables such as wealth and income can be obtained from the next HRS wave. For example, HRS 2002 collects information on total income for the year 2001 which coincides with the information on consumption in CAMS 2001. Since HRS 2012 is not available yet, I exclude CAMS 2011 from the analysis.

For the analysis, I select an unbalanced panel sample of households in which the respondent and, if present, his/her spouse were working either full-time or part-time in 2001. The HRS sample introduced in Section 5.2 includes the households in which the respondent and the spouse (if present) were working in 1992. The sample in this section consists of individuals from the original HRS cohort who were first interviewed in 1992 and were still working in 2001 as well as younger cohorts who entered the survey in the subsequent waves (see footnote 49 for details).

Based on the labor force status information reported in the CAMS survey I define retirement and unretirement as explained in Section 5.2. The final sample consists of 678 households which also have non-missing information on nondurable spending and on the covariates used in the analysis. Among these households 369 were couples and 309 were singles in 2001, for a total of 1047 working individuals. Among these individuals 563 of them have become retired during the observation period 2001-2009 (53.77 percent). 97 individuals re-entered the labor force after a retirement spell (17.23 percent). The unretirement rate in this sample is smaller than the unretirement rate in the HRS sample used in the main estimation probably because the observation period is relatively shorter.

Table 5.7 illustrates median total nondurable spending around the time of retirement and unretirement of men and women used in the analysis.[59] I do not report separate analysis for couples and singles due to small number of observations. The categories of nondurables are home insurance, property tax, rent, electricity, water, heat, home repair services, phone/cable/internet, auto insurance, health insurance, house/yard supplies, home repair supplies and services, food, dining out, clothing, gasoline, vehicle services, drugs, health services, medical supplies, vacations, tickets, hobbies, contributions, and gifts.

According to Table 5.7 men's and women's retirements are associated with a drop in household income which is about 33 percent and 30 percent, respectively. On the other hand, household total nondurable spending falls with the men's retirement by 8 percent whereas it falls with women's retirement by 5 percent. The drop in nondurable

[59] The number of categories of the nondurable spending differs across waves. For example, in wave 2 new categories of nondurable spending such as personal care products and gardening and housekeeping services were added to the survey. To compare nondurable spending over time I use the categories that are available in all waves of the CAMS survey.

consumption is much smaller than the drop in income suggesting that individuals have enough savings to smooth their consumption around retirement. Table 5.7 also reveals that household income is 11 percent higher when men become unretired while it increases by 3 percent when women become unretired. The small increase in income with unretirement is reasonable given that post-retirement jobs pay much less than pre-retirement jobs (Maestas 2010). The descriptive statistics in Table 5.7 also suggests that men's unretirement is associated with an increase in nondurable spending by 12 percent whereas women's unretirement does not change expenditures on nondurables substantially. The reason behind the increase in nondurable spending at unretirement could be the increase in work-related expenses such as expenses on dining out, clothing, gasoline, and vehicle services.

Table 5.7: Median real annual spending on nondurables and income, couples and singles together

	Household Income						**Household Nondurable Spending**					
	Males						Males					
	Retirement in wave 0			Unretirement in wave 0			Retirement in wave 0			Unretirement in wave 0		
waves	No. Obs	Median	% change	No. Obs	Median	% change	No. Obs	Median	% change	No. Obs	Median	% change
-1	237	49520		41	43352		237	21992		41	21420	
0	237	33410	-33	41	48221	11	237	20219	-8	41	24087	12
1	145	33719	1	21	48457	0	145	19198	-5	21	17394	-28
	Females						Females					
	Retirement in wave 0			Unretirement in wave 0			Retirement in wave 0			Unretirement in wave 0		
waves	No. Obs	Median	% change	No. Obs	Median	% change	No. Obs	Median	% change	No. Obs	Median	% change
-1	326	40052		56	31867		326	20589		56	19662	
0	326	28064	-30	56	32693	3	326	19635	-5	56	19160	-3
1	145	35987	28	22	26122	-20	145	23421	19	22	17506	-9

Notes: Nondurable spending categories are divided by the OECD-modified equivalence scale, couples' household income is divided by 1.5 because household income is the respondent's income plus his/her spouse's income for couples. Both income and spending are in 2004 dollars.

Table 5.8 gives estimation results for the consumption and income equations by OLS estimation. I do not instrument actual labor market status since one of the instruments which is individuals' expectations of work during retirement, is only available in 1992 and, therefore, I do not observe this variable for the younger cohorts who entered the survey in subsequent years.

Table 5.8: Estimation of household nondurables spending, couples and singles together

	(1) Change in log nondurable spending OLS	(2) Change in log food spending OLS	(3) Change in log income OLS
Change in couple dummy	0.186	0.136	-0.373*
	(0.174)	(0.159)	(0.216)
Change in household size	0.022	0.028	-0.027
	(0.017)	(0.025)	(0.017)
(Men, Age)/10	0.005	-0.001	0.001
	(0.004)	(0.006)	(0.006)
(Women, Age)/10	0.002	0.004	0.001
	(0.006)	(0.01)	(0.01)
Men, become retired	-0.029	-0.072	-0.374***
	(0.037)	(0.060)	(0.069)
Women, become retired	0.040	-0.133***	-0.275***
	(0.032)	(0.051)	(0.067)
Men, become unretired	0.077	-0.028	0.221**
	(0.079)	(0.126)	(0.096)
Women, become unretired	0.029	0.175	0.012
	(0.067)	(0.114)	(0.130)
Constant	-0.046	0.106	0.006
	(0.047)	(0.083)	(0.088)
Number of observations(households)	2027(678)	2002(672)	2027(678)

Standard errors in parentheses are robust to the presence of heteroscedasticity. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Year dummies are included. Food consumption includes food at home and food eating out.

According to the results in Table 5.8, household income drops by 37 percent and 28 percent with men's and women's retirement, respectively, suggesting a higher replacement rate for women than men. As it is displayed in Table 5.6, the reductions in household income with men's and women's retirement are 22 percent and 16 percent in the HRS sample which consists of the original HRS cohort born between 1931 and 1941 and their spouses. As mentioned above, the CAMS sample includes the original HRS cohort as well as younger cohorts. The lower replacement rates for men and women in the CAMS sample than in the HRS sample may suggest that younger cohorts have lower replacement rates than older cohorts. One reason behind this finding can be that younger cohorts are more likely to hold a defined contribution (DC) pension plan as in the United States, like in other countries, the percentage of workers covered by a DC pension plan has been increasing over time. Unlike the DB plan holders who receive a fixed amount of retirement benefits during retirement, DC plan holders face a greater uncertainty about their retirement income due to uncertainty about the rate of return on their accumulated retirement savings.

Although younger cohorts have lower replacement rates at retirement, the findings in Table 5.8 show that they do not experience a fall in their nondurable spending, suggesting that they are able to smooth their consumption around retirement. The finding of this paper that there is no significant drop in nondurable spending at retirement is in line with the findings by Hurd and Rohwedder (2008). Using the first three waves of the CAMS survey they find that the drop in nondurable spending at retirement is negligible and the size of the drop could be explained by mechanisms such as the cessation of work-related expenses, home production and efficient shopping or unexpected retirement due to a health shock.

Table 5.8 also reveals that household income does not change when women become unretired whereas men's unretirement is associated with a 22 percent increase in household income. On the other hand, neither men's nor women's unretirement is associated with a significant increase in expenditures on nondurables. Finally, the findings under the second column in Table 5.8 indicate that women's retirement reduces household food consumption by 13 percent while men's retirement does not change food consumption significantly. Moreover, regardless of gender, food consumption does not change with unretirement. The findings regarding food consumption are in line with the findings reported in Table 5.6. Overall, the findings in this section suggest that households do not experience a fall in nondurable spending around retirement and they do not start consuming more at the time of unretirement.

5.5.2.2 Narrower definition of retirement

As discussed in Section 5.2, this paper uses a broader definition of retirement in the sense that the individuals who are unemployed, disabled, or not in the labor force are assumed to be fully retired. This definition may overstate the importance of unretirement since under this definition the re-entries from unemployment are categorized as unretirement transitions. In this section I re-estimate the equation (5.10) for the HRS sample, using a narrower definition of retirement. Under this definition I exclude individuals who are unemployed, disabled, or not in the labor force from the estimation sample instead of treating them as fully retired. The new sample includes 2,310 households and 3,570 individuals who were working in 1992. Among these individuals 1,946 have become retired during the observation period 1992-2010 (54.51 percent). 535 individuals have re-entered the labor force after a retirement spell which corresponds to 27.49 percent of the retirees. Under broader definition of retirement, unretirement rate was 31.64 percent which is slightly higher than 27.49 percent. Estimation results are given in Table 5.9.

Table 5.9: Estimation results with narrower definition of retirement, couples and singles together

	(1) Change in log consumption OLS	(2) Change in log income OLS	(3) Change in log consumption GMM
Change in couple dummy	0.317***	0.540***	0.317***
	(0.048)	(0.062)	(0.049)
Change in household size	0.105***	-0.003	0.104***
	(0.010)	(0.010)	(0.011)
(Men, Age)/10	0.001	0.005**	0.001
	(0.002)	(0.002)	(0.004)
(Women, Age)/10	0.002	0.001	0.003
	(0.002)	(0.005)	(0.005)
Men, become retired	-0.006	-0.226***	0.023
	(0.018)	(0.027)	(0.093)
Women, become retired	-0.061***	-0.151***	-0.061
	(0.018)	(0.024)	(0.125)
Men, become unretired	0.023	-0.050	-0.044
	(0.040)	(0.066)	(0.272)
Women, become unretired	0.048	0.102**	-0.101
	(0.041)	(0.042)	(0.377)
Constant	-0.014	0.012	-0.018
	(0.021)	(0.036)	(0.023)
Number of observations (households)	9,095(2,310)	9,095(2,310)	9,095(2,310)
Hansen's J test (p-value)			3.779 (0.436)
Partial F test			
Men, become retired			233.57
Women, become retired			230.23
Men, become unretired			31.71
Women, become unretired			38.33
AP F test for weak identification			
Men, become retired			35.05
Women, become retired			16.28
Men, become unretired			25.08
Women, become unretired			18.23
Test of exogeneity- χ^2_4 *(p-value)*			7.027 (0.134)

Standard errors in parentheses are robust to the presence of heteroscedasticity.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Year dummies are included.

According to these results, the main findings in Table 5.6 seem to be robust to the narrower definition of unretirement. I find that the household food consumption does not change with the men's retirement or unretirement whereas it slightly decreases with the women's retirement only.

5.5.2.3 Separate estimations for couples and singles

In this section I estimate the consumption equation described in equation (5.10) for couple and single households separately.[60] Table 5.10 reports the estimation results for couple households.

Table 5.10: Estimation of household food spending, couples

	(1) Change in log consumption OLS	(2) Change in log income OLS	(3) Change in log consumption GMM
Change in household size	0.071***	0.019	0.071***
	(0.009)	(0.012)	(0.011)
(Men, Age)/10	-0.014	-0.038	-0.003
	(0.016)	(0.025)	(0.021)
(Women, Age)/10	0.019	-0.014	0.012
	(0.012)	(0.015)	(0.010)
Men, become retired	-0.033*	-0.164***	-0.120
	(0.0191)	(0.023)	(0.150)
Women, become retired	-0.058***	-0.163***	0.075
	(0.021)	(0.023)	(0.105)
Men, become unretired	0.053	-0.045	-0.222
	(0.038)	(0.052)	(0.385)
Women, become unretired	0.005	0.099**	0.205
	(0.047)	(0.043)	(0.231)
Constant	-0.024	0.350***	-0.055
	(0.090)	(0.126)	(0.088)
Number of observations(households)	5,624(1,343)	5,624(1,343)	5,624(1,343)
Hansen's J test (p-value)			5.606 (0.231)
Partial F test			
Men, become retired			189.29
Women, become retired			147.10
Men, become unretired			33.59
Women, become unretired			29.21
AP F test for weak identification			
Men, become retired			15.51
Women, become retired			28.38
Men, become unretired			5.69
Women, become unretired			12.89
Test of exogeneity- χ^2_4 *(p-value)*			3.915 (0.417)

Standard errors in parentheses are robust to the presence of heteroscedasticity. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Year dummies are included.

[60] I do not report separate results for single males and females since there are a few single males in the sample (only 256 males are single).

The estimation results for couples are very similar to those reported in Table 5.6, suggesting that the main estimation results are driven largely by couple households. One major difference is that the AP F statistic for weak identification in the unretirement equation of men is smaller than 10, which may imply that this equation is weakly identified. If the instruments do not strongly predict the endogenous variables, the estimated coefficients are biased similar to the OLS estimates, and therefore, the GMM results are not reliable. The p-value of the exogeneity test statistic in Table 5.10 indicates that the exogeneity of the right-hand-side variables cannot be rejected. On the other hand, if there is a weak identification problem, one cannot rely on the validity of the exogeneity test. Although the estimation results for couples are in line with the main estimation results, the results based on GMM estimation should be interpreted with some caution.

Table 5.11: Estimation of household food spending, singles

	(1) Change in log consumption OLS	(2) Change in log income OLS	(3) Change in log consumption GMM
Change in household size	0.144^{***}	-0.001	0.142^{***}
	(0.014)	(0.014)	(0.016)
Age/10	0.039	0.012	0.033
	(0.028)	(0.039)	(0.023)
Become retired	-0.070^{***}	-0.231^{***}	-0.181
	(0.026)	(0.037)	(0.196)
Become unretired	-0.004	0.061	-0.671
	(0.041)	(0.068)	(0.542)
Constant	-0.236	-0.083	-0.179
	(0.166)	(0.223)	(0.141)
Number of observations (households)	4,673 (1,118)	4,673(1,118)	4,673(1,118)
Hansen's J test (p-value)			0.506 (0.776)
Partial F test			
Become retired			306.14
Become unretired			55.69
AP F test for weak identification			
Become retired			32.39
Become unretired			14.14
Test of exogeneity- χ^2_2 *(p-value)*			13.437 (0.001)

Standard errors in parentheses are robust to the presence of heteroscedasticity. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Year dummies are included.

As it is shown in Table 5.11, in single households, individuals' retirement is associated with a drop in income by 23 percent and a drop in consumption by 7 percent. The drop in consumption does not necessarily contradict with the predictions of the life-cycle model because this effect is a combination of expected and unexpected retirements.

The p-value value of the exogeneity test statistic in Table 5.11 shows that the exogeneity of the right-hand-side variables is rejected, suggesting that the GMM estimation is more reliable than the OLS estimation. According to finding based on the GMM estimation retirement or unretirement does not change the level of food consumption significantly.

5.6 Conclusions

The earlier studies from the UK and the US concluded that individuals experience a drop in consumption at retirement even if the retirement is anticipated. In this paper, I re-investigate the drop in consumption at retirement, the so-called retirement consumption puzzle, by taking into account the fact that individuals may re-enter the labor force after being retired. For this purpose I use nine waves of the HRS survey which represents the population of Americans over age 50 and their spouses. This paper has several important findings. In contrast with the earlier studies in the literature, this paper does not find a significant drop in food consumption at retirement when retirement is fully anticipated. I also find that men's observed retirement is not associated with a significant drop in food consumption, yet household food consumption decreases by about 7 percent when women become retired expectedly or unexpectedly. This finding could be explained by women's contribution to home production. Household food spending may decrease during women's retirement since women spend more time on meal preparation and shopping than men. This paper also analyzes how nondurable spending respond to changes in individuals' labor market status. I find that retirement is not associated with a significant drop in nondurable spending in line with the predictions of the life cycle theory of consumption. The finding that consumption does not respond to retirement also suggests consumption and leisure are additively separable.

In contrast with the previous studies, I also investigate how consumption changes when individuals re-enter the labor force after retirement. I find that neither food nor nondurable spending changes with unretirement. One of the reasons behind this finding could be that individuals' income does not increase significantly when they unretire probably because post-retirement jobs pay much less than pre-retirement jobs. Therefore, it is not surprising to see that individuals' consumption does not increase significantly. Another reason could be that unretirement is an anticipated event for the majority of the individuals in the sense that individuals' expectations of work during retirement strongly predict their future transition to unretirement, on average. As a result, one may expect that consumption does not change with unretirement since anticipated income changes do not affect individuals' level of consumption according to the life-cycle theory of consumption.

Overall, the findings of this paper suggest that individuals are forward-looking and they have saved enough to smooth their consumption around retirement, on average. A larger drop in food expenditures with women's retirement can be explained by women's contribution to home production during retirement. A further research can be done to investigate how men and women differ in time spent on meal preparation and shopping before and after retirement. Similarly, one can also examine whether unretirement is associated with a decrease in time spent on home production. The CAMS survey has detailed information on time spent on several activities such as food preparation and shopping and, therefore, it can be used to investigate these issues in the future.

5.A HRS questions on food expenditures

Questions asked to the respondents who receive food stamps

-How many dollars' worth of food stamps did you (or other family members now living here) get last month?

-In addition to what you bought with food stamps, did you (or other family members now living here) spend any money on food that you use at home? If so, how much? Was that per month, year, or what?

-In addition to that, did you have any food delivered to the door? If so, how much did you spend on that food? Was that per month, year, or what?

-About how much do you (and other family members now living here) spend eating out, not counting meals at work or at school? (The answer can be nothing or an actual value) Was that per week, month, or what?

Questions asked to the respondents who do not receive food stamps

-About how much do you (and other family members living here) spend on food that you use at home in an average week? Was that per week, month, or what?

-Do you have any food delivered to the door which isn't included in that amount? If so, how much did you spend on that food? Was that per week, month, or what?

-About how much do you (and other family members now living here) spend eating out, not counting meals at work or at school? (The answer can be nothing or an actual value) Was that per week, month, or what?

5.B Total income by gender

Table 5.B.1: Mean and Median of Total Income in 2004 dollars

	Couples		**Singles**	
	Men	Women	Men	Women
Mean total income	40342	23678	74162	25239
Median total income	31865	18076	26166	20008
Number of observations (Individuals)	7,294(1,343)	7,294(1,343)	1,321(256)	4,707(862)

Total income is the sum of individuals' income from all sources (salary, pension, unemployment etc.)

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Nederlandse samenvatting

In de meeste geïndustrialiseerde landen vergrijst de bevolking als gevolg van onder meer een stijgende levensverwachting. Deze vergrijzing heeft in veel van deze landen tot pensioenhervormingen geleid. In Nederland, bijvoorbeeld, is besloten de AOW gerechtigde leeftijd stapsgewijs te verhogen van 65 jaar in 2012 naar 67 jaar in 2023. Tevens zijn de regels rondom vervroegd pensioen (VUT en prepensioen) aangescherpt, dit alles met het doel oudere werknemers zolang mogelijk actief op de arbeidsmarkt te houden. In veel andere landen zijn soortgelijke hervormingen doorgevoerd zoals bijvoorbeeld in de Verenigde Staten waar met name de door werkgevers gesubsidieerde pensioenen minder genereus zijn geworden. Deze ontwikkelingen leiden voor een individu tot een grotere onzekerheid ten aanzien van het te verwachten pensioeninkomen dan in het verleden het geval was. Een typisch kenmerk van de voorgestelde of al geïmplementeerde hervormingen is dat er meer individuele verantwoordelijkheid gevraagd wordt ten aanzien van de financiële voorbereiding op de jaren na pensionering.

De vier hoofdstukken van dit proefschrift gaan over het verschil tussen objectieve en subjectieve levensverwachting, consumptiebeslissingen van ouderen, pensioneringsgedrag, en over sparen voor pensioen.

Aangezien meer verantwoordelijkheid wordt verwacht van mensen om in hun eigen pensioen te voorzien is het van belang te weten of mensen hun levensverwachting op een correcte manier inschatten. Derhalve wordt in hoofdstuk 2 onderzocht in hoeverre individuele subjectieve en objectieve levensverwachtingen met elkaar in overeenstemming zijn. In een enquête afgenomen onder Nederlandse huishoudens wordt de subjectieve levensverwachting gemeten voor alle volwassenen van het huishouden door te vragen naar de kans op overleven tot bepaalde leeftijden. Indien deze zogenaamde subjectieve overlevingskansen nauwkeurig de objectieve levensverwachting van een persoon kunnen bepalen dan zullen economische beslissingen die inzicht in levensverwachting vereisen in dit opzicht optimaal zijn. In dit hoofdstuk en in hoofdstuk 3 wordt gebruikt gemaakt van de DHS (DNB Household Survey) aangevuld met administratieve gegevens over de datum van overlijden van DHS deelnemers. De belangrijkste bevinding van hoofdstuk 2 is dat Nederlandse mannen en vrouwen hun levensverwachting onderschatten met, respectievelijk, gemiddeld één en acht jaar. Deze onderschatting heeft implicaties voor economische beslissingen van personen. Bijvoorbeeld, indien een persoon denkt niet zo oud te worden terwijl de kans hierop groter is dan hij of zij zelf inschat, dan zal deze persoon gemiddeld te weinig sparen om het gewenste bestedingsniveau na pensionering te behouden tot het moment van overlijden en/of besluiten om eerder te stoppen met werken dan optimaal is.

In hoofdstuk 3 onderzoek ik de redenen voor de onderschatting door Nederlandse mannen en vrouwen van hun levensverwachting. Met name onderzoek ik of deze onderschatting in Nederland van de levensverwachting gedeeltelijk kan worden verklaard door een gebrek aan kennis van de gemiddelde levensverwachting van mannen en vrouwen in Nederland (de populatie levensverwachting). De belangrijkste bevinding van dit hoofdstuk is dat het onderschatten van de populatie levensverwachting een significante rol speelt bij het onderschatten van de eigen levensverwachting. Een persoon die een betere kennis heeft van de populatie levensverwachting kan zijn of haar eigen levensverwachting beter inschatten: een één jaar nauwkeurigere kennis van de populatie levensverwachting is geassocieerd met een half jaar nauwkeurigere inschatting van de eigen levensverwachting. Deze bevinding suggereert dat indien personen beter geïnformeerd worden over de populatie levensverwachting ze hun eigen levensverwachting beter inschatten en zodoende betere economische beslissingen kunnen nemen waarbij de levensverwachting een rol speelt, zoals spaar- en pensioneringsbeslissingen.

Hoofdstuk 4 onderzoekt de rol van subjectieve levensverwachting (op basis van subjectieve overlevingskansen) bij het nemen van consumptiebeslissingen van ouderen. Een eenvoudig levenscyclus model zonder onzekerheid voorspelt dat het niveau van consumptie bepaalt wordt door het inkomen dat men gedurende het hele leven heeft ontvangen. Onder de aanname dat het inkomen in een werkzaam jaar hoger is dan de jaarlijkse pensioenuitkering, voorspelt dit model dat mensen sparen als ze jong zijn en ontsparen na pensionering. Eerdere studies vinden echter geen empirisch bewijs voor deze voorspelling dat ouderen ontsparen en zelfs niet indien alleen naar ouderen op zeer hoge leeftijd wordt gekeken. In de literatuur is het eenvoudige levenscyclus model uitgebreid om deze discrepantie tussen theorie en empirie te verklaren. Hurd (1989, 1999) verklaart het spaargedrag van alleenstaande ouderen en (echt)paren door het eenvoudige levenscyclus model uit te breiden met onzekerheid in levensduur en een erfenis motief. Dit hoofdstuk toetst de voorspellingen van de modellen van Hurd (1989, 1999) voor Amerikaanse ouderen. Hiervoor wordt gebruik gemaakt van gegevens van de Health and Retirement Study (HRS) die zijn aangevuld met gegevens van de Consumption and Activities Mail Survey (CAMS). Een van de belangrijkste bevindingen is dat meer dan de helft van de gepensioneerde personen in de steekproef meer dan hun pensioenuitkering besteden en dus ontsparen zoals een (eenvoudig) economisch model voorspelt. De bevindingen met betrekking tot de rol van de subjectieve sterftekansen laten voor alleenstaande personen zien dat de consumptiegroei afneemt bij een hogere subjectieve sterftekans. Deze bevinding is zoals het gebruikte economisch theoretische model voorspelt. Voor (echt)paren vind ik echter geen relatie tussen consumptiegroei en subjectieve sterftekans. Een reden voor deze laatste bevinding kan zijn dat de aanname van eenzelfde relatieve risico aversie voor beide personen in het huishouden te restrictief is aangezien vrouwen over het algemeen meer risico avers zijn dan mannen bij het nemen van financiële beslissingen. Op basis van alle bevindingen tezamen zou je kunnen stellen dat ouderen ontsparen na pensionering.

In hoofdstuk 5 onderzoek ik de sterke afname in bestedingen bij pensionering (de zogenaamde "retirement-consumption puzzle"). Door de bestedingen rondom het moment van pensionering te onderzoeken kan er inzicht verkregen worden in hoeverre personen genoeg hebben gespaard voor bestedingen (consumptie) na hun pensionering. Indien personen na hun pensionering minder besteden dan ervoor dan kan dit betekenen dat ze niet voldoende hebben gespaard. Eerder onderzoek nam aan dat indien een persoon met pensioen gaat deze niet meer op de arbeidsmarkt actief zal zijn. Echter, in sommige landen komt het de laatste decennia steeds vaker voor dat gepensioneerden terugkeren naar de arbeidsmarkt. In de Verenigde Staten, bijvoorbeeld, keert 26 procent van de gepensioneerden terug naar de arbeidsmarkt. Er kan dus een vertekend beeld ontstaan door alleen de bestedingen rondom het moment van pensionering te onderzoeken en geen rekening te houden met een eventuele terugkeer naar de arbeidsmarkt. Bijvoorbeeld, een oudere werknemer die bij een reorganisatie gedwongen is te stoppen met werken (vervroegd pensioen) zal waarschijnlijk een negatieve inkomensschok ervaren en kan besluiten om weer terug te keren naar de arbeidsmarkt om zijn of haar bestedingen op peil te houden. In dit hoofdstuk onderzoek ik daarom ook de bestedingen van gepensioneerden rondom het moment dat ze weer terugkeren naar de arbeidsmarkt. Hiervoor maak ik gebruik van negen golven van de Health and Retirement Study (HRS) dat een representatieve steekproef vormt van Amerikanen ouder dan 50 jaar en hun eventuele partners over de jaren 1992-2010. Hoofdstuk 5 heeft een aantal belangrijke bevindingen. De beslissing om terug te keren naar de arbeidsmarkt na pensionering wordt significant beïnvloed door financiële factoren zoals het opgebouwde vermogen op het moment van pensionering en of de persoon een werkgeverspensioen heeft en hoe dit pensioen gefinancierd is (beschikbare premie- of uitkeringssysteem). In tegenstelling tot eerdere studies vind ik geen afname in de bestedingen aan voedingsmiddelen wanneer pensionering een geanticipeerde gebeurtenis is. Ik vind echter wel een daling in de bestedingen aan voedingsmiddelen met ongeveer 7 procent indien een vrouw met pensioen gaat (ongeacht of dit geanticipeerd was of niet). Deze afname kan verklaard worden door de bijdrage die een vrouw levert aan eigen productie (“home production”). Een bevinding in lijn met de voorspelling van een eenvoudig levenscyclus model is dat bestedingen niet veranderen indien een persoon zijn of haar terugkeer naar de arbeidsmarkt al had gepland (een geanticipeerde gebeurtenis). Alle bevindingen van dit hoofdstuk tezamen suggereren dat huishoudens genoeg hebben gespaard om de bestedingen rondom pensionering op peil te houden (“consumption smoothing”).

Curriculum Vitae

Vesile Kutlu Koç was born on December 10, 1984 in Salihli, Turkey. In 2010 she obtained her Master's degree in Economics and Finance of Aging at Tilburg University. In the fall of 2010 she enrolled in the Research Master's program in Economics at Tilburg University. The title of her Research Master's thesis was 'Essays on subjective well-being and retirement behavior' and she was awarded the Netspar prize for the best Research Master thesis. After she graduated in July 2011, she started her PhD in Economics at Utrecht University School of Economics in September 2011. Her PhD project was financed by the Network for Studies on Pensions, Aging and Retirement (Netspar).

Vesile Kutlu Koç's research interests are economics of aging, retirement behavior, life expectancy and consumption decisions of the elderly. As of September 2014 she works as a post-doctoral researcher at the Munich Center for the Economics of Aging (MEA) in Munich, Germany.

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