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Subjective mortality hazard shocks and the adjustment of consumption expenditures

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Abstract

I estimate the effect of shocks to subjective mortality hazards on consumption expenditures of retired individuals using the Survey of Health, Ageing and Retirement in Europe. I measure mortality expectations with survey responses on survival probabilities. To create plausibly exogenous variation in mortality hazard, I use the death of a sibling as an instrument. My results show that survey responses contain economically relevant information about longevity expectations, and confirm the predictions of life-cycle theories about the effect of these expectations on intertemporal choice.

Keywords: consumption decisions, subjective longevity, IV estimation

JEL classification: C26, D91, J14

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1 Introduction

Life expectancy at older ages is increasing. Increasing longevity has important consequences on the consumption and saving decisions of elderly people. The standard life-cycle model with mortality risk implies that if people's longevity expectations change then their optimal level of consumption also changes.

In this paper I analyse the adjustment of consumption expenditures of elderly people following changes in their subjective longevity. In particular, I analyse whether consumption is adjusted after a mortality hazard shock, and if this adjustment is in line with the implications of the life-cycle model. The paper is related to empirical works which analyse consumption and saving profiles based on life-cycle models with mortality risk, and to the literature on applying subjective probability data in empirical economic models. The paper contributes to the understanding of consumption behavior at older ages, and also to the application of subjective expectations data in empirical economic models.

I build a life-cycle model in which life expectancy is stochastic. Based on this model the ex ante effect of mortality risk on the expected consumption growth is negative: those who face higher mortality hazard plan lower consumption level for the future and consume more in the present, provided that credit constraints are not binding. This result builds on the findings of Yaari (1965), who was the first to show that under certain circumstances lifetime uncertainty can act analogously to increased impatience, and Hurd (1989), who derives and shows empirically that wealth is negatively responsive to mortality rates. Another implication of my model is that an upward shock to mortality hazard affects the consumption level positively: an increase in the hazard implies that it is optimal to consume more in the present, thus consumption should be adjusted. A novelty of my paper is to test this second implication of the life-cycle model. The individual level estimation results provide evidence for the predictions of life-cycle theories about the effect of subjective mortality hazards on intertemporal choice. A related model of consumption level is estimated by Skinner (1985a), who estimates positive effect of mortality on consumption. De Nardi et al. (2006) find that both differential life expectancy and expected medical expenditures have notable effect on asset accumulation. My paper contributes to this line of the literature in estimating the effect of shocks to mortality hazards.

I use the first two waves of the Survey of Health, Ageing and Retirement in Europe (SHARE) in the empirical analysis. The empirical specifications are based on the life-cycle model. Based on the SHARE data I can use the reported subjective survival probability to generate a subjective hazard indicator. Survey data was first used by Hamermesh (1985) to investigate the determinants of subjective survival probabilities. In line with the findings of Hamermesh (1985), Hurd and McGarry (1995), and Smith et al. (2001), I also find evidence using the SHARE data that subjective life expectancy corresponds to actuarial life expectancy, and that subjective probabilities covary with observable risk factors. My results also confirm that subjective longevity measures can be reasonably used in empirical analyses on economic decisions. This is in line with Manski (2004), who argues for applying subjective probabilistic data in empirical work. Post and Hanewald (2011) also use the SHARE data in analyzing subjective survival probabilities, however, they focus on longevity risk (measured by the dispersion of survival expectations) and its relation to the wealth level.

To my knowledge, this is the first paper to estimate the adjustment of consumption expenditures after a mortality hazard shock on micro level data. Based on studies that use aggregate data, there is no consensus about the effect of increasing longevity on the aggregate consumption expenditures and savings (see e.g. Skinner (1985b), Li et al. (2007), and Tobing (2012)). Using micro level subjective survival data can provide further insights into the effects of changing longevity, as it allows me to identify the effect of changing longevity. I instrument the change in mortality hazard by the death of a sibling. The instrumenting strategy hinges on the assumption that the death of a sibling influences the subjective survival probability, and such an event does not have direct effect on the consumption expenditures of the elderly people. Robustness tests and data checks support using the death of a sibling as instrument. Potential endogeneity of the instrument is assessed by examining the robustness of results to bequest from siblings, cohabitation with siblings, endogenous changes in surviving sibling preferences, and non-random attrition.

Gan et al. (2004), Bloom et al. (2007) and Salm (2010) use subjective survival probabilities from the Health and Retirement Study (HRS) in the empirical analysis of life-cycle models. My main contributions are estimating the effect of changing subjective mortality hazard on consumption expenditures, and using a novel instrumenting strategy to address identification concerns. While the basic research question of Gan et al. (2004) is the empirical analysis of bequest motives, they also find that subjective survival probabilities can explain the observed consumption and saving decisions better. Bloom et al. (2007) show that household wealth increases with subjective survival probabilities. They instrument the survival probability with the age or age at death of parents. Using the death of a sibling as instrument is more appropriate in my empirical analysis than following the instrumenting strategy of Bloom et al. because of weak instrument and potential endogeneity problems. Salm (2010) also investigates the effect of subjective life expectancy on the consumption and saving decisions of older people, without applying the method of instrumental variables. He also finds that the explanatory power of subjective expectations on consumption dynamics is higher than that of the statistical life table data.

My empirical results show that those who have positive wealth holdings adjust their consumption expenditures upwards if their subjective mortality hazard increases. Assuming that the adjustment of consumption expenditures after increasing and decreasing mortality hazard is symmetric, the empirical results also indicate that increasing perceived longevity leads to smaller consumption expenditures, hence to slower wealth decumulation. The reliance of consumption decisions on subjective longevity also implies that full annuitisation might not be optimal. The estimated ex ante effect of mortality hazard on consumption dynamics is more sensitive to the empirical specifications, but again some evidence is found for the life-cycle effect.

The rest of the paper is organised as follows. In Section 2 I present the life-cycle model with mortality risk, which provides implications for the empirical analysis. The data and the variables used are presented in Section 3. The estimation results and potential caveats are discussed in Section 4. Robustness checks are provided in Section 5, and Section 6 concludes.

2 The life-cycle model of consumption with uncertain lifetime

The purpose of this section is to derive implications for the empirical analysis. Closely related models are developed by Hurd (1989), Gan et al. (2004) and Salm (2010). The main novelty of the here presented life-cycle model is that I derive the effect of mortality hazard shocks on the optimal level of consumption. I present a simple model in which there is a single composite consumption good. Income uncertainty, medical expenditures and bequest motives are neglected. Some extensions of the model are discussed in Section 5.4.

Consumption and income realisations take place at the beginning of each time period, whereas death can happen at the turning points to new periods. I assume that there are no credit facilities and income is of annuity type, which are reasonable assumptions for older, retired individuals.[1] As the model explains the consumption decisions of retired individuals, labour supply decisions are not considered here. The maximisation problem of individual i is:

$$\max_{\{C_{it},t=0...T_i\}} E_0 \sum_{t=0}^{T_i} I_{it}\beta^t U(C_{it})$$
$$\text{s.t. } W_{it} = R(W_{it-1} - C_{it-1} + Y_i)$$
$$0 \leq W_{it}, \forall t = 1...T_i. \tag{1}$$

C_{it} is consumption at time t, Y_i is income, W_{it} is wealth, β is the discount factor, and R is one plus the interest rate. E_0 denotes expectations at time 0. I_{it} is a binary indicator which equals one if individual i is alive at time t, zero otherwise. The expected value of this indicator is the subjective survival probability. T_i is the maximum remaining years of life for individual i. The consumption, wealth, and income variables are conditional on survival to the given period, otherwise these values are zero. $U(C_{it})$ is the utility from consumption, assumed to be increasing and concave in C_{it}.

The only uncertainty in the model is mortality risk. Individuals form expectations on their survival, and these expectations are subject to shocks, thus life expectancy is

[1] At the aggregate level and in the long run, increasing longevity can affect the income level partly through intergenerational transfers (see Hock and Weil (2012) for such an analysis).

stochastic. I assume that individuals make their expectations on future survival using all the available information. Using the law of iterated expectations, the expected value of future survival probability equals the current expectation on the survival, i.e. $E_0\left(E_t(I_{t+k}|I_t=1)\right)=E_0(I_{t+k}|I_t=1)$. This implies that only the current survival probabilities matter in the maximisation problem. Based on these considerations, the maximand of model (1) can be rewritten:

$$\max_{\{C_{it},t=0\ldots T_i\}} \sum_{t=0}^{T_i} E_0\left(I_{it}\right)\beta^t U(C_{it}). \tag{2}$$

Another rationale for this simplification is that I_t is either 0 or 1. If $I_t=0$ then $U(C_t)=0$, thus only the $I_t=1$ state matters, which occurs with probability $E_0(I_t)$.

Let's assume that the utility of current consumption is of the constant relative risk aversion form: $U(C_{it})=C_{it}^{1-\gamma}/(1-\gamma)$, where $\gamma>0$. Using the law of iterated expectations and assuming that the credit constraint is not binding give the Euler equation:

$$C_{it}=C_{i0}E_0(I_{it})^{\frac{1}{\gamma}}\left(\beta R\right)^{\frac{t}{\gamma}}. \tag{3}$$

Equation (3) holds only if wealth is not zero, otherwise the consumption equals the income in every period. The Euler equation reflects that a consequence of lifetime uncertainty is that future is discounted to a higher extent. The Euler equation describes the expected consumption path, conditional on survival. However, the Euler equation per se cannot reflect the effect of changing survival probability on the optimal consumption path.

The next step is to derive the optimal level of current consumption. I assume that the expected value of the survival indicator is a power function of the life table survival probability. This assumption is equivalent to the hazard-scaling approach of Gan et al. (2005). Let η_{i0} denote the individual specific index of pessimism at time 0, and S_t^{t+k} the life table survival probability from time t to time $t+k$. To simplify notations, I denote the subjective survival probability of individual i from time t to time $t+k$ with s_{it}^{t+k}, thus $E_0(I_{it}) = s_{i0}^t$. It follows that $s_{i0}^t = (S_0^t)^{\eta_{i0}}$. Denoting individual i's subjective cumulative hazard of dying between periods t and $t+k$ with h_{it}^{t+k}, and using the definition that $\ln s_{it}^{t+k} = -h_{it}^{t+k}$, equation (3) can be rewritten:

$$\ln C_{it+1} - \ln C_{it} = \frac{1}{\gamma}\ln(\beta R) - \frac{1}{\gamma}h_{it}^{t+1} = \frac{1}{\gamma}\ln(\beta R) + \frac{1}{\gamma}\eta_{i0}\ln S_t^{t+1}. \tag{4}$$

No general closed form solution exists for the optimal consumption level, because it might be optimal to deplete the wealth at some point during the lifetime, and from that point on the Euler equation does not hold. However, conditional on the time of depletion ($T_i^* \leq T_i$), a closed form solution can be derived for the optimal consumption level. Since there is no bequest motive, wealth is depleted at time T_i, at the latest. It is optimal not to deplete the wealth before T_i if the ratio of initial wealth holdings (W_{i0}) to income (Y_i) is large, and if the expected remaining lifetime of the individual is high (for details see also Hurd (1989)). T_i^* depends also on the discount and interest factors, and on the coefficient of relative risk aversion.

Using the $W_{iT_i^*} = 0$ condition gives that

$$\sum_{t=0}^{T_i^*}\left(-\frac{C_{it}}{R^t} + \frac{Y_i}{R^t}\right) + W_{i0} = 0. \tag{5}$$

I assume that the Euler equation holds exactly until time T_i^*, wealth is depleted with consumption C_{iT^*} at T_i^*, and from that point on the consumption equals the income.[2] Substituting the Euler equation from equation (3) into equation (5) and using the hazard-scaling assumption give the expression of optimal current consumption:

$$C_{i0} = \frac{W_{i0} + Y_i \frac{1-R^{T_i^*+1}}{R^{T_i^*}-R^{T_i^*+1}}}{\sum_{t=0}^{T_i^*} \frac{\left(S_0^t\right)^{\frac{\eta_{i0}}{\gamma}} (\beta R)^{\frac{t}{\gamma}}}{R^t}}. \tag{6}$$

Based on this expression the partial effect of the pessimism index on the level of initial consumption is positive, thus the partial effect of subjective hazard is also positive.

My aim is to analyse the effect of unexpected changes in subjective hazard on consumption level. A hazard shock can be represented by a change in the pessimism index (η_i). I assume that an upward shock affects the subjective hazard at the beginning of period one, which is represented by increasing η_{i0} to η_{i1}.[3] First I also assume that the time point of wealth depletion is only marginally affected by the hazard shock, and remains approximately equal to T_i^*. It can be derived using the expression of optimal initial consumption level (equation (6)) that the optimal consumption level at period one is

$$C_{i1} = RC_{i0} \frac{\sum_{t=0}^{T_i^*} \frac{\left(S_0^t\right)^{\frac{\eta_{i0}}{\gamma}} (\beta R)^{\frac{t}{\gamma}}}{R^t} - 1}{\sum_{t=1}^{T_i^*} \frac{\left(S_1^t\right)^{\frac{\eta_{i1}}{\gamma}} (\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}}}. \tag{7}$$

Using that $S_0^t = S_0^1 \cdot S_1^t$, it follows that the ex post difference between the consumption

[2] There are two decison variables: C_{i0} and T_i^*. Based on the assumption of exact depletion, $C_{iT_i^*} = Y_i$, and $C_{iT_i^*} = C_{i0}\left(S_0^{T_i^*}\right)^{\frac{\eta_{i0}}{\gamma}} (\beta R)^{\frac{T_i^*}{\gamma}}$ from the Euler equation. Thus $Y_i/C_{i0} = \left(S_0^{T_i^*}\right)^{\frac{\eta_{i0}}{\gamma}} (\beta R)^{\frac{T_i^*}{\gamma}}$, which shows that given income and initial consumption, T_i^* has to decrease if the mortality hazard increases (i.e. η_{i0} increases).

[3] This representation implies that the shock has a permanent effect in the sense that the survival probabilities to each future periods are affected. If instead only the short run expectations change then the effect on consumption level has the same sign but smaller magnitude.

levels of the first two periods is

$$\ln C_{i1} - \ln C_{i0} = \frac{1}{\gamma}\ln(\beta R) - \frac{1}{\gamma}h_{i0}^{1} + \ln\left(\sum_{t=1}^{T_i^*}\frac{\left(S_1^t\right)^{\frac{\eta_{i0}}{\gamma}}(\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}}\right) - \ln\left(\sum_{t=1}^{T_i^*}\frac{\left(S_1^t\right)^{\frac{\eta_{i1}}{\gamma}}(\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}}\right). \tag{8}$$

If the credit constraint is not binding then the differenced logarithmic consumption depends negatively on the initial hazard level, but an upward hazard shock ($\eta_{i1} > \eta_{i0}$) has positive effect on it. This solution is based on the assumption that the hazard shock does not considerably affect the optimal time point of wealth depletion. If T_i^* is large, and the hazard shock is moderate then equation (8) can be a good approximation for the consumption dynamics. In addition, if the ratio of initial wealth to income is high then $T_i^* = T_i$ is also unaffected. Otherwise T_i^* decreases after the upward hazard shock, which makes the last term in equation (8) even smaller. Thus the expression under equation (8) can be considered as a lower bound of the ex post difference in the optimal logarithmic consumption expenditures.[4]

I apply linear approximation of the differenced logarithmic term in equation (8) at η_{i0}:

$$\ln\left(\sum_{t=1}^{T_i^*}\frac{\left(S_1^t\right)^{\frac{\eta_{i0}}{\gamma}}(\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}}\right) - \ln\left(\sum_{t=1}^{T_i^*}\frac{\left(S_1^t\right)^{\frac{\eta_{i1}}{\gamma}}(\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}}\right) \approx$$

$$\approx \left(\sum_{t=1}^{T_i^*}\frac{\left(S_1^t\right)^{\frac{\eta_{i0}}{\gamma}}(\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}}\right)^{-1}\left(\sum_{t=1}^{T_i^*}\frac{\left(S_1^t\right)^{\frac{\eta_{i0}}{\gamma}}(\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}}\left(-\eta_{i1}\ln S_1^t + \eta_{i0}\ln S_1^t\right)\right). \tag{9}$$

Since $-\eta_{i1}\ln S_1^t$ equals the cumulative hazard from period 1 to period t after the hazard

[4] If wealth is allowed to be depleted before time T_i then the solution of the consumption model can be found only numerically. Numerical results indicate that the effect of an upward hazard shock on consumption expenditures is positive, and an upward hazard shock might decrease T_i^*.

The upward shift in the optimal consumption level depends on the parameters in the model. Holding the income fixed, if the wealth level is higher then the optimal consumption level is more sensitive to the hazard shock. The sensitivity is not a monotone function of the coefficient of relative risk aversion, but at higher relative wealth holdings the effect of shock decreases with the risk aversion coefficient.

shock and $-\eta_{i0} \ln S_1^t$ equals the cumulative hazard before the hazard shock, substituting equation (9) to (8) implies that the first differenced logarithmic consumption depends positively on the first differenced mortality hazard.

Motivated by the consumption model of equation (8), and using the approximation of equation (9), I will estimate two empirical specifications:

$$d \ln C_{i1} = \alpha_{01} + \alpha_{11} h_{i0} + \alpha_{21} dh_{i1} + X_i \alpha_{31} + u_{1i} \tag{10}$$

$$d \ln C_{i1} = \alpha_{02} + \alpha_{12} h_{i0} + \alpha_{22} H_i + X_i \alpha_{32} + u_{2i}. \tag{11}$$

Although these specifications are based on a set of simplifying assumptions, the joint inclusion of initial hazard and hazard shock measures correspond to the life-cycle model. In these models h_{i0} and h_{i1} are the one period hazard indicators at time 0 and 1, and in the second specification H_i is a binary indicator of increasing hazard between periods 0 and 1.[5] The vector of X_i includes additional control variables. As a simplification, I neglect the heterogeneity in the effect of changing hazard. Based on the life-cycle model the α_{11} and α_{12} parameters are negative, whereas the α_{21} and α_{22} parameters should be positive if the credit constraint is not binding. If the credit constraint is binding then these parameters should be zero. Model (10) is based on the linear approximation of equation (8), whereas model (11) allows me to test the implication of the life-cycle model that the consumption expenditures should increase after an upward hazard shock.

The consumption model extended with hazard shocks is comparable to those consumption models in the literature where the consumption differences depend on intertemporal

[5] Using dh_{i1} in equation (10) is also a simplification, which can support the interpretability of the empirical results. Apart from hazard shocks, the hazard increases due to ageing between two dates of observation, which effect is also included in dh_{i1}, but not in $-\eta_{i1} \ln S_1^t + \eta_{i0} \ln S_1^t$. The sign of the estimated effect of changing hazard is robust to this simplification. If the two indicators of changing hazard are cleared from the effect of ageing then their estimated effects become stronger.

substitution, and also on changing expectations about future income. The adjustment of consumption after shifts in permanent income is analysed among others by Flavin (1981) and Campbell and Deaton (1989). Parker and Preston (2005) decompose consumption growth into four factors, one of which is the effect of new informations. Here I assume that the individual income is constant, but analyse the adjustment after changing subjective mortality hazard, which can also be considered as adjustment after the arrival of new informations.

3 Data

The empirical analysis is based on the first two waves of the Survey of Health, Ageing and Retirement in Europe.[6] The SHARE is a cross-national panel database covering individuals aged at least 50, and their spouses. The first wave of the data was collected in year 2004, and the survey is repeated every second year. I include those countries in the analysis for which both the first and second wave data are available: Austria, Belgium, Denmark, France, Germany, Greece, Italy, the Netherlands, Spain, Sweden, and Switzerland.

When estimating the consumption models I exclude those respondents who are aged above 80 in the second wave (around 7% of the sample). The reason for this restriction is that the subjective mortality hazard indicator is less reliable for the oldest individuals. I also exclude those respondents who report to be employed or self-employed in either of the two survey waves (around 35% of respondents aged $50-80$). For this restricted sample

[6]This paper uses data from SHARE release 2.3.1, as of July 29th 2010. SHARE data collection in 2004-2007 was primarily funded by the European Commission through its 5th and 6th framework programmes (project numbers QLK6-CT-2001- 00360; RII-CT- 2006-062193; CIT5-CT-2005-028857). Additional funding by the US National Institute on Aging (grant numbers U01 AG09740-13S2; P01 AG005842; P01 AG08291; P30 AG12815; Y1-AG-4553-01; OGHA 04-064; R21 AG025169) as well as by various national sources is gratefully acknowledged (see http://www.share-project.org for a full list of funding institutions).

the assumption of annuity type income is more reasonable. The following statistics and results refer to the restricted estimation sample, however, in Section 5 I present robustness checks with respect to the age and employment restrictions.

3.1 Variables used

Table 1 includes descriptive statistics of the variables used in the empirical analysis. The number of observations varies due to item nonresponse. The financial variables are purchasing parity adjusted annual amounts, deflated to year 2005 Euros. These variables are generated as the mean of the five imputed values provided in the SHARE database. The household level consumption, income and wealth measures are scaled by the household size. In this scaling I assign a value of 1 to the first household member, and 0.7 to each of the further household members.

- Table 1 about here -

Consumption is measured by annual expenditure on food at home and outside home.[7] Outlying consumption values are excluded from the empirical analysis, where an observation is defined to be outlier if the absolute value of the first differenced consumption is larger than 5 thousand EUR (3% of the observations). Measuring consumption by expenditures on food is a data limitation since the second wave of SHARE does not provide panel data on overall or other categories of consumption expenditures.[8] The

[7] The wording of the question is the following: "Thinking about the last 12 months: about how much did your household spend in a typical month on food to be consumed at/outside home?" This amount is multiplied by 12 to generate the annual amount.

[8] Alternatively, the empirical analysis could also be based on the HRS merged with the Consumption and Activities Mail Survey. These data include subjective survival probability measures and more general consumption measures, as well. However, the identification strategy applied here does not work with these alternative data. Based on the Rand HRS data file (version L, waves 5-10), the death of a sibling does not have significant effect on the first differenced subjective hazard, and its effect on the binary indicator of hazard shock is positive but small with a p-value of 0.08. This difference from the SHARE findings can be due to more severe measurement errors, different reporting styles, or less tight family relationships among siblings.

food expenditure indicator can serve as a proxy for overall consumption expenditures, and measures of expenditure on food can be relatively reliable. If the utility function is additively separable in food and other consumption goods then the results of the life-cycle model of consumption are valid for food consumption. Additive separability is assumed by Zeldes (1989) when testing the permanent income hypothesis. Browning and Lusardi (1996) provide a literature overview of Euler equation consumption studies, and document that using food consumption data is widespread in the literature. On the other hand, Mork and Smith (1989) and Attanasio and Weber (1995) provide evidence that food consumption might not be an adequate measure when analysing the sensitivity of consumption to income, or when estimating the elasticity of intertemporal substitution. The main concern is that as food consumption is a necessity, expenditures on food are likely to be more stable than on other consumption categories. This implies that the estimation results in this paper might be biased towards zero - the adjustment of total consumption expenditures after a hazard shock is likely to be larger than the adjustment of expenditures on food.

The indicators of new chronic diseases are binary variables which equal one if the individual reports having heart attack, stroke, hip fracture or the diagnosis of high blood pressure, cancer, diabetes, high blood cholesterol since the first interview. Two additional health measures are limitations with activities of daily living (ADL), and whether the respondent suffers from depression. The becoming single indicator is set to one if the respondent was married and living together with the spouse in the first wave, but his marital status is widowed, divorced or married but living separated from the spouse in the second wave.

The variable of central interest is the subjective survival probability. The wording of the survival probability question is "What are the chances that you will live to be age [target age] or more?", where the target age depends on the age of the respondent (with values between $75 - 110$).

In Table 1 I also include some descriptive statistics on the number of siblings and death of siblings, as the instrumenting strategy is based on these variables.

3.2 Measuring subjective hazard

The reported survival probability can change between the two waves not only if the subjective remaining life expectancy changes, but also if the target age in the probability question changes. Therefore the reported probabilities should be adjusted.

I adjust the reported probability so that for each individual it represents the subjective probability of living at least two years more. I do not make any further adjustment, assuming that the reported probability includes all the available information about the subjective survival beliefs. I apply a similar adjustment method as Salm (2010). The adjustment procedure is based on the hazard-scaling approach of Gan et al. (2005), which also corresponds to the assumptions made in the life-cycle model of Section 2. The first step is to derive the individual specific index of pessimism:

$$\eta_i = \frac{\ln s_{it}^{t+a}}{\ln S_t^{t+a}}, \tag{12}$$

where t is the current age, $t + a$ is the target age, s is the subjective survival probability, and S is the life table survival probability. I use the WHO life tables for year 2006, which are gender and country specific life tables.[9]

[9] Source: http://apps.who.int/whosis/database/life_tables/life_tables.cfm. These are period (or current), and not cohort life tables. Period life tables might underestimate the survival probabilities to old ages. Since the life tables are used only for adjusting the reported probabilities, using period life tables does not cause bias in the estimates.

The 2-year subjective survival probability of individual i is calculated the following way:

$$s_{it}^{t+2} = \left(S_t^{t+2}\right)^{\eta_i}, \tag{13}$$

and the 2-year cumulative hazard is

$$h_{it}^{t+2} = -\eta_i \ln S_t^{t+2}. \tag{14}$$

The 2-year difference between the target and current age is specified because two years elapse between the first and second survey waves.

5.5% of the respondents of the estimation sample report 0% survival probability in either the first or second wave survey, for whom the pessimism index and mortality hazard cannot be calculated. When estimating the consumption models I exclude those respondents for whom the subjective hazard is missing, but in Section 5.1 I analyse the sensitivity of the results to this exclusion.

- Figure 1 about here -

The histograms of the reported and generated survival probabilities for the estimation sample (aged 50-80, retired) are presented in Figure 1, where the assumption is used that the 0% reported probability corresponds to 0.5% true probability. The adjusted survival probability is more skewed to the right than the original one because it refers to 2-year survival probability, whereas the mean of the difference between the current and target age is 13.5. The histogram of the reported survival probabilities shows the problem of focal responses (0, 50 or 100 percentage reported probabilities), which indicates measurement error.

Based on the WHO life tables the survival probabilities can be determined only for 5-year age ranges. In order to calculate the survival probability to any age I make the simplifying assumption that the number of people alive from a given cohort declines linearly within the given 5-year intervals.

- Figure 2 about here -

Figure 2 depicts the median of the subjective and life table 2-year survival probabilities by age for the retired individuals. It indicates that the reported probabilities fit the life table probabilities relatively well, and the 2-year survival probabilities are close to one, especially at younger ages. However, people tend to overestimate their survival probability at older ages, whereas there is slight underestimation at younger ages.

In Table 2 I present the estimated coefficients of three OLS models. These models show how the subjective hazard indicators correspond to the death of relatives, to the parents' longevity, and to other individual specific characteristics. As there are no endogeneity concerns in these models (reverse causality is not likely and the measurement errors in the dependent variables can be assumed to be independent of the regressors), OLS specification is appropriate. In the first part of the table I use two indicators of increasing hazard: the first differenced adjusted hazard ("diff. hazard"), and a binary indicator of an at least 1.5 percentage points drop in the adjusted subjective survival probability between the first and second waves of the survey. The binary indicator of increasing hazard equals one for 33% of the respondents in the estimation sample. In the second part of the table the dependent variable is the first wave adjusted hazard. The significance levels are based on clustered standard errors, with clustering on the household level.

- Table 2 about here -

My focus is on the indicators of the death of a sibling between the two survey waves, and the death of all siblings before wave one. For 12% of the respondents in the estimation sample the number of siblings alive decreases between the two waves, and the observed decrease is less than three. The change in the number of siblings alive is a noisy measure, therefore I consider as noise the differences higher than three. The level of first wave hazard is regressed among others on a binary variable which equals one if the respondent has no siblings alive in wave one, but reports that he had siblings before (6% of the respondents in the estimation sample).

Based on these estimations the respondents update their survival probabilities if a sibling dies. The estimation results imply that for a 60 year old representative man the expected remaining lifetime decreases by around 2.7 years after the death of a sibling, ceteris paribus. The estimation results also indicate that if the respondent had siblings but all of them are dead by wave one then the subjective mortality hazard is significantly higher.[10]

The presented results are in line with the findings of Hurd and McGarry (1995) and Hamermesh (1985): the observed health problems have positive effect on the measure of subjective hazard, and the subjective hazard depends on the longevity of the relatives.

4 Estimation results

4.1 Empirical specification

In this paper I analyse how the hazard level and increasing mortality hazard affect the consumption expenditures of older individuals. The estimated models are equations (10) and (11). I use two indicators of increasing hazard: the first differenced adjusted hazard, and a binary indicator of an at least 1.5 percentage points drop in the adjusted two-year subjective survival probability between the first and second waves of the survey. As the

[10]The rest of the included regressors have mostly the expected sign. Due to measurement errors (as also reflected by the focal responses), the estimation results of the models of changing hazard are noisier than the results of the hazard level model, and the explanatory power of the regressions is small. There are some unexpected results, e.g. the negative coefficient of a new diagnosis with diabetes. The negative sign can be due to changing health behavior after the diagnosis (e.g. healthier diet), but can be also caused by measurement errors among the 300 newly diagnosed respondents.

cutoff value of 1.5 in the increasing hazard indicator is selected arbitrarily, I present in Section 5.2 some robustness checks with respect to this value. The X_i vector includes indicators of individual-specific preferences or changes in preferences. These variables are age, age squared, gender, having children, first differenced logarithmic income, indicators of being diagnosed with chronic diseases since the first wave, ADL limitation and depression, becoming single, and country dummies. I also include the death of the father or mother as explanatory variables since such an event might influence the consumption expenditures e.g. through bequests.

Unobserved shocks (e.g. unobserved changes in health status or macroeconomic shocks) can affect not only the consumption dynamics but also the reported survival probability, making the first differenced hazard endogenous in the model. In addition, the subjective survival probability is measured with error, as a consequence, the hazard indicators are also measured with error. If the measurement error is correlated with the observed hazard values then the OLS estimator is biased. These endogeneity concerns call for the application of the method of instrumental variables. The key assumption needed for the validity of the applied instrumenting method is that the instruments used (indicators of a sibling's death) are independent from the error term of the consumption model (which consists of the unobservables and the measurement error).

4.2 First stage results

The death of a sibling between the two survey waves is used as instrument for the first differenced hazard and for the binary indicator of increasing hazard. Even if the death of a sibling might have been expected (e.g. due to long lasting illness), this event causes an exogenous shock to the subjective survival probability. It affects the subjective hazard, and the death of a sibling is unlikely to have direct effect on food consumption expenditures at older ages. The latter might not be true for the parents or the children of the respondent. Table 2 also shows that the effect of the death of a parent on the first differenced hazard is insignificant and smaller than the effect of the death of a sibling. The level of first wave hazard is instrumented by a binary variable which equals one if the respondent has no siblings alive in wave one, but reports that he had siblings before. Using binary instruments does not violate the consistency of the IV estimator. I discuss some potential endogeneity concerns in Section 4.4.[11]

Bloom et al. (2007) apply a different instrumenting strategy: they instrument the subjective survival probability with the age or age of death of the parents, using HRS data. However, as the parents and their children are likely to share some consumption expenditures, their age or age at death is more likely to directly affect the consumption expenditures, thus might not be a valid instrument in the consumption model. Nevertheless, as a specification test I re-estimate my models applying the instruments of Bloom et al. in Section 5.3.

In Table 3 I present the coefficients of the instruments from the first stage of the consumption model. This table refers to the specification of equation (10), where the differenced hazard is a regressor. First I estimate the model for the whole retired population aged $50-80$, then I restrict the sample to those who have positive wealth holdings, according to the net worth indicator. I present the estimation results with no additional controls, then including age and age squared as controls, and finally including all control variables listed above. I present also the value of the F-test, where the null hypothesis is that the two instruments are jointly insignificant.

[11] The instrumental variable models are estimated and tested by the *ivreg2* command of Stata, as provided by Baum et al. (2007).

- Table 3 about here -

Table 4 presents the selected first stage coefficients from the model of equation (11).

- Table 4 about here -

The results show that under all specifications the death of a sibling between the two survey waves increases the subjective hazard, and the subjective hazard in the first wave is significantly higher if all the siblings of the respondent have died by that time. The magnitude and the significance of these effects are not affected by restricting the sample to the wealthy individuals. The instruments are generally weaker if additional controls are included in the consumption models.

4.3 Second stage results

I estimate the consumption models on the whole applicable sample and also on the sample of individuals with positive wealth holdings. The theory predicts that the consumption expenditures of wealthy individuals are more responsive to the hazard shocks. Due to the endogeneity concerns I apply the method of IV estimation. For the sake of comparison I reestimate the models with OLS.

In the first set of specifications I include the differenced hazard as a measure of increasing hazard (equation (10)). The estimated coefficients of interest are presented in Table 5. The estimations are repeated with the dummy variable of increasing hazard included as a regressor (equation (11)). The estimated coefficients of interest based on this specification are reported in Table 6. The explanatory power of the consumption models is small, due to the noisy measure of first differenced consumption expenditures.

- Table 5 about here -

If the differenced hazard is included as regressor in the consumption model (Table

5) then the expected positive effect of this indicator cannot be seen based on the OLS estimates. Based on the IV estimation results the partial effect of the differenced hazard on consumption expenditures is positive, but this effect is significant at 5% level only for those who are not credit constrained. This is in line with the life cycle model: if someone lives only from the annuity type income then the consumption is unaffected by the subjective mortality hazard. The results suggest that the ex post effect of subjective hazard on consumption expenditures is stronger than the ex ante effect. The estimated effects of the hazard measures are qualitatively robust to the inclusion of the additional control variables.

- Table 6 about here -

According to the implications of the life-cycle model, increasing mortality hazard indicated by a drop in the survival probability should lead to increased consumption expenditures. The estimation results show the expected sign of this effect if the indicator of increasing hazard is instrumented, but the effect is significant only at 10% significance level once age is controlled for (Table 6).

Based on the presented results it is clear that using instrumental variables when estimating the effect of subjective hazard on consumption is important. The smaller magnitude of the OLS estimates can be due to omitted variable bias (e.g. unobserved health shocks increasing subjective hazard but decreasing consumption expenditures), and can also be due to measurement errors (attenuation bias). Since the probability of the death of a sibling increases with the respondent's age, and age can have direct (possibly nonlinear) effect on consumption decisions, in the preferred IV specification I control for age and age squared. Omitting the other control variables is also reasonable since those are generally insignificant under the second stage.[12] The preferred specifications indicate

[12] I present in the Appendix the detailed IV estimation results, restricting the sample to those with

that the consumption path is influenced by the hazard shocks.

The magnitude of the estimated effect of a hazard shock is not negligible. Around the median expenditure, if the logarithmic value of food consumption expenditures decreases or increases by 0.6 due to a large shock in expected longevity then that is equivalent to $110 - 200$ EUR change in the individual monthly food expenditures.[13]

For a 60 year old man a 1.5 percentage points decrease in the two-year survival probability is approximately equivalent to 4 years decrease in the expected remaining lifetime (from 21 years to 17 years), and to 0.02 increase in the two-year subjective hazard.[14] The increasing hazard can be partly due to ageing, but is also due to the arrival of new information. Based on the IV results presented in the middle part of Table 5, such a decrease in the expected longevity leads to around 270 EUR increase in the annual expenditure on food at the median, ceteris paribus, if the wealth holdings are not zero. This corresponds to an adjustment of around 9%. The model extended with additional controls predict a higher increasing effect, around 300 EUR. If the two-year subjective hazard increases by the same amount in addition to the increase due to ageing then the estimated adjustment in consumption expenditures is even higher.

The estimated coefficient of the first wave hazard is negative both under the OLS and IV estimates, but its magnitude is sensitive to the estimation method and to the included indicator of hazard shock. The negative sign is in line with the Euler equation: people with higher mortality hazard allocate more consumption expenditures to the present and

positive wealth. I test the joint significance of the control variables other then the hazard and age indicators. The p-value of the Chi-squared statistic is 0.61 (if the differenced hazard is included) and 0.37 (if the binary indicator of increasing hazard is included).

[13] The estimated effect of increasing hazard is a "local average treatment effect" if there is a systematic difference between those who update their expectations after a sibling's death and those who do not. In this paper I use the simplifying assumption that the effect of a hazard shock on the logarithmic consumption expenditures is constant across the analysed population.

[14] These calculations are based on the German life table. It is assumed that before the hazard shock the subjective survival probability of this individual was equal to the life table survival probability.

less to the future. The estimated coefficient of the initial hazard under the IV estimation is between -1.066 and -5.251. This implies that if a 60 year old man had initially median food expenditures but 1 percentage point lower two-year survival probability than a similar man with life-table survival probability then the man with the lower survival probability is expected to allocate $30 - 160$ EUR less expenditure on food to the next observed period (i.e. the second next year), ceteris paribus. However, these estimated effects are statistically not significant.

4.4 Endogeneity concerns

The validity of the instrumenting strategy is violated if the death of a sibling has direct effect on the consumption expenditures.

The consumption measure might be directly affected by the death of the sibling if the sibling lived in the same household as the respondent. Therefore I reestimate the consumption models with excluding from the estimation sample the respondents whose household size changed between the two waves (14% of the sample). I also reestimate the models with excluding those individuals who report receiving gift or inheritance of 5 thousand EUR or more since the first wave, and for whom it can be identified that it was received from a sibling (less than 0.3% of the sample). Neither of these restrictions influences the estimated sign of the indicators of changing subjective hazard, and the size of the estimated effect is qualitatively unaffected.

Another concern can be that the expected inheritance from parents might increase after the death of a sibling. If this is the case then such increase in expected income can cause the adjustment of consumption expenditures. However, the data do not provide any evidence for this hypothesis. Even if the sample is restricted to those who have a parent alive (14% of the estimation sample), the death of a sibling has no significant effect on the reported probabilities of receiving any inheritance or inheritance above 50 thousand EUR within the next ten years. Based on this subsample the estimated increase in the probability of receiving inheritance after a sibling's death is not only statistically insignificant but also of relatively small magnitude, 0.5 percentage points for any inheritance, and 2.2 percentage points for large inheritance. These results indicate that the positive effect of a hazard shock on consumption expenditures is not driven by a direct influence of the death of the sibling on the consumption expenditures.

If the consumption preferences change after the death of a sibling then that can also violate the exogeneity of the instrument. In two related studies Elder (2007) finds some evidence that subjective longevity increases the risk tolerance of the HRS respondents, and Finkelstein et al. (2008) provide evidence that the marginal utility of consumption increases with health.

In this paper consumption is measured by the expenditure on food consumed at and away from home. If the two categories of food expenditures are adjusted differently after the hazard shock then that can indicate that the preferences change either with the death of a sibling or with the hazard shock. Based on the available data it is not possible to distinguish these two influencing mechanisms from each other. For the sake of analysing how the preferences change after the death of a sibling, I reestimate the consumption model with using the expenditure on food consumed at home as consumption measure. The average share of expenditures on food consumed at home within the total food expenditures is 89% in the sample. Table 7 presents the estimated hazard coefficients if the differenced logarithmic value of expenditure on food consumed at home is the dependent variable. In these models I include age and age squared as control variables, and IV estimation is applied. The expenditure on food consumed at home is estimated to be adjusted upwards after the hazard shock slightly more than the total expenditure.

- Table 7 about here -

Thus the estimated positive effect of an upward hazard shock on consumption expenditures is driven by the effect on the expenditure on food consumed at home. The adjustment can take place both through quality and quantity (e.g. so as to facilitate the invitation of guests). However, as the estimated effect of a hazard shock is close to the benchmark result, and the standard errors of the coefficient estimates are relatively large, there is no clear statistical evidence for a change in consumption preferences.

4.5 Selectivity

If the sample is nonrandom then that can potentially cause bias in the estimated coefficients. As documented by Borsch-Supan et al. (2008), the attrition rate between the first two waves of the survey is 31.7%. The majority of the attrition is not due to death, only 2.6% of wave one respondents deceased between the two waves. Attrition is more likely for individuals with higher subjective mortality hazard in the first wave of the sample.

The nonresponse rate to subjective survival probability in the estimating sample is relatively high, around 9%. The item nonresponse rate varies across the countries, it is the highest in France (20%), the lowest in Austria (4%), based on both waves of the survey, excluding the respondents aged above 80 and those who are still working. A probit model of item nonresponse indicates that the probability of not answering the survival probability question is higher for those who are older and who report worse health status.[15]

[15] The indicator of noresponse is set to one if the differenced survival probability is missing. The control variables besides the country dummies are age, age squared, gender, marital status, education level, income, and self reported health status. I also control for the interviewer's observation of declining

If the selection into the sample is related to the instruments, and if the consumption dynamics are systematically different between the included and missing observations then the IV estimates are biased. Observations on the consumption decisions near the end of life are likely to be missing. Thus the effect of increasing mortality hazard indicator is underestimated if consumption becomes more responsive to the hazard near the end of life. This can be the case if the uncertainty in survival probability decreases with approaching the end of life. On the other hand, the effects are overestimated if the marginal utility of consumption approaches zero before death.

The estimated effect of an upward hazard shock is stronger if the first wave hazard was above the median hazard. This result suggests that the effect of a hazard shock is likely to be underestimated due to attrition and item nonresponse among respondents with higher first wave mortality hazard.

5 Robustness and specification checks

5.1 Estimation sample

In the following robustness and specification checks the sample is restricted to retired individuals with positive wealth holdings, and only the IV estimates are analysed. In Table 8 I present the results of the IV estimations where age and age squared are controlled for. The first row includes the reference results from Section 4.3.

As the first robustness check, I reestimate the models with including in the sample those who are aged above 80 but not more than 90. The magnitude of the estimated coefficients are strongly affected by the age restriction. One explanation for the sensitivity

willingness to answer during the interview. This is reasonable since the expectation questions are in the final block of the SHARE questionnaire.

of the coefficients is the different explanatory power of the instruments: the effect of the death of all siblings on the first wave hazard becomes stronger, whereas the effect of the death of a sibling on the hazard shock indicators become weaker with the inclusion of the oldest respondents. A second explanation can be that people aged above 80 are less likely to adjust their consumption expenditures after an upward shock in the subjective hazard, which is reflected by the insignificant and small coefficients of the indicators of changing hazard.

- Table 8 about here -

In the benchmark specifications the hazard indicators are missing if the reported survival probability is zero (5.5% of the estimation sample). Due to rounding the zero reported probability might correspond to very low but nonzero true subjective survival probability. I reestimate the models using the assumption that the reported zero probability corresponds to 0.5% survival probability to the target age. The sign of the estimated adjustment after a hazard shock is unaffected by this modification. The estimated effect of the differenced hazard becomes weaker, whereas that of the binary indicator of increasing hazard becomes stronger. These findings suggest that the observed zero survival probabilities are due to measurement error, to which the differenced hazard measure is more sensitive than the binary indicator of increasing hazard.

In the third robustness check I repeat the benchmark specification with the difference that the individuals with positive wealth are selected not based on the net worth but on the financial wealth measure. If the non-financial wealth is illiquid and cannot be used for financing consumption needs then the credit constraint can become binding also for those who report positive net worth but zero financial wealth holdings. The coefficients reported in Table 8 indicate that the estimated effect of a hazard shock is qualitatively robust to the choice of wealth category.

The presented checks indicate that it is a robust finding that consumption expenditures are adjusted upwards if the subjective hazard increases. This adjustment is much weaker for the oldest individuals. The negative coefficient of the first wave hazard is also a robust finding.

5.2 Cutoff values of increasing hazard

In this paper I set the binary indicator of increasing hazard to one if the two-year survival probability drops at least by 1.5 percentage points between the first two waves of the survey. Here I analyse the sensitivity of the estimation results with respect to this cutoff value. First I reestimate the preferred IV model with using the cutoff value of 1 percentage point decrease, then with a cutoff value of 2. In the first case the indicator of increasing hazard equals one for 38% of the respondents in the estimating sample, in the second case this ratio is 29%. The estimated coefficients of interest are reported in Table 8.

The estimated effect of increasing hazard increases slightly if a higher cutoff value is used. This is a reasonable finding as it shows the effect of more substantial hazard shocks. On the other hand, the statistical significance of the estimated effect becomes weaker, which corresponds to the lower number of individuals categorised as being subject to a hazard shock.

5.3 Instrumental variables methods

The next set of specification checks is with respect to the applied method of instrumental variables. Since there is some evidence that the instruments are weak, it is reasonable to compare the results with alternative estimators. Weak instruments can cause large bias in the finite sample two-stage least squares estimates. Hahn et al. (2004) suggest the usage of Fuller's estimator with parameters 1 or 4.[16] An alternative can be the jackknife instrumental variables estimator (JIVE), which can mitigate the finite-sample bias of the 2SLS estimator. I apply the method suggested by Angrist et al. (1999) where the jackknife first stage fitted value is used as instrument in the second stage IV estimation. These results are presented in the last part of Table 8.[17]

It is a robust finding that the estimated effect of increasing mortality hazard is positive on consumption expenditures. The effect of the hazard shock is estimated to be larger if the jackknife instrumental variables estimator is used. The results also reinforce that the ex ante effect of subjective hazard on the consumption path is negative. However, this effect is insignificant under all specifications.

Finally, I re-estimate the preferred specifications with using the age or age at death of the parents and the death of a parent between the two survey waves as instruments. These instruments correspond to the instrumenting strategy of Bloom et al. (2007), although their validity is questionable in the current application. The positive estimated effect of hazard shocks still hold under this alternative instrumenting strategy, although the estimated effect is no longer significant.

These results altogether suggest that the adjustment of consumption expenditures after a hazard shock can be reliably estimated by the preferred 2SLS estimation method.

[16] Fuller's estimator is a member of the k-class estimators. If the structural model is $Y = X\beta + u$, then the k-class estimator is $\hat{\beta} = (X'(I - kM_Z)X)^{-1} X'(I - kM_Z)Y$. Here Z is the vector of first stage regressors, and $M_Z = I - P_Z = I - Z(Z'Z)^{-1} Z'$. The OLS estimator is obtained if $k = 0$, the 2SLS is obtained if $k = 1$. The LIML estimator is obtained if $k = \lambda$, where λ is the smallest eigenvalue of the matrix $W'P_Z W(W'M_Z W)^{-1}$ with $W = [Y, X]$.

In Fuller's estimator $k = \lambda - a/(N - K)$, where N is the number of observations, and K is the number of regressors in the first-stage model. If $a = 1$ then the model is approximately unbiased, if $a = 4$ then there is bias, but the mean squared error is smaller. Further details about these estimation methods are provided by Davidson and MacKinnon (1993) and Hahn et al. (2004).

[17] The *jive* command of Stata written by Poi (2006) is applied in the jackknife estimation.

5.4 Extensions of the life-cycle model

The life-cycle consumption model derived in Section 2 is based on the assumption that the decision makers have annuity income. The implications of the model might not hold if income is time varying. For instance, if the credit constraint is binding for an individual who expects increasing income then the expected consumption path can be positively sloped. The optimal consumption path is also modified if income is uncertain. The planned consumption path becomes flatter or even positively sloped with income uncertainty, in which case the previously derived positive effect of increasing hazard might not hold. The intuition for this result is that income uncertainty necessitates precautionary savings, and consumption is postponed to later ages when the uncertain income is realised.

As an indicator of time varying income I use the employment status of the respondents. The results presented in this paper are based on the subsample of retired individuals. The data provide evidence that the effect of increasing hazard on consumption expenditures is indeed stronger for those who are not employed. The estimated coefficient of the differenced hazard becomes 4.41 (previously 5.67), and the coefficient of the dummy of increasing hazard becomes 0.47 (previously 0.60) in the preferred specifications if the employed respondents are also included in the estimation (the size of the estimation sample after this extension is around 12.5 thousand). Both coefficients are significant at 10% significance level, but insignificant at 5%. As in reality the retired individuals might still be subject to income shocks (e.g. through income sources from other household members), the main results of this paper are likely to underestimate the pure effect of mortality hazard shocks.

The presented life-cycle model also assumes that there are no bequest motives. Hurd (1989) and Gan et al. (2004) find using HRS data that bequest motives are weak. If the life-cycle model is extended with bequest motive then the model can be solved only numerically. However, a simple two-period model indicates that the partial effect of mortality hazard on the consumption level becomes smaller with bequest motives.[18]

An indicator of bequest motive is whether the respondent has children or not. It can be assumed that the bequest motives are weaker for those who do not have children. However, only 10% of the respondents fall into this category, and due to the small sample the consumption model coefficient estimates become imprecise with t statistics close to zero. The similar holds if the bequest motives are indicated by living in non single households. Restricting the sample to single households would necessitate the exclusion of 83% of the otherwise eligible observations.[19]

6 Concluding remarks

The life-cycle model with uncertain lifetime predicts that the effect of subjective mortality hazard on expected consumption dynamics is negative, whereas an upward shock in mortality hazard leads to higher consumption expenditures, provided that the credit constraint is not binding. The main novelty of this paper is to identify the influencing role of changing hazard on consumption expenditures. Using the first two waves of the

[18] The following simplifying assumptions are made in the two-period life-cycle model. The utility of bequest has the same functional form as that of consumption, but multiplied with an individual-specific multiplicator (B_i). This term indicates the strength of the bequest motive. In the first period the individual decides on the current consumption level, and in the second period he either consumes all the remaining wealth (if survives) or leaves bequest (if dies).

Under these assumptions the sign of the effect of subjective hazard on the optimal consumption level is the same as the sign of $(1 - B_i)$, provided that the credit constraint is not binding. Therefore the partial effect of mortality hazard is smaller if bequest motives are stronger.

[19] An alternative approach could be to use the reported subjective probability of leaving inharitance. However, it is not obvious that this measure indicates bequest motives, it suffers from measurement errors similarly to the subjective survival probability, and again the majority (around 75%) of the respondents indicate positive probability.

Survey of Health, Ageing and Retirement in Europe, I identify the effect of the subjective hazard by using indicators of the death of a sibling as instruments.

The empirical results confirm the implication of the life-cycle model about the effect of increasing mortality hazard. People aged $50-80$, who have positive wealth holdings are estimated to adjust their consumption expenditures after an upward hazard shock. The magnitude of this effect is not negligible, and the positive estimated effect of increasing mortality hazard on consumption expenditures is a robust result. The estimated effect is stronger if the employed individuals are excluded from the sample. If the effect of increasing and decreasing subjective hazard on consumption expenditures is symmetric, then the estimation results also indicate that increasing expected longevity leads to smaller consumption expenditures, hence to slower wealth decumulation. My results also confirm that survival probabilities reported by survey respondents contain economically relevant information about longevity expectations. The findings about the dependence of consumption expenditure decisions on subjective expectations are also relevant to annuitisation decisions. Full annuitisation is not optimal if individuals have better information on their expected longevity than the insurance companies have, and my results provide evidence that subjective longevity indeed matters in economic decisions.

Some evidence is also found for the negative effect of first period mortality hazard on the consumption dynamics, which is implied by the Euler equation of the life-cycle model. However, this estimated ex ante effect is more sensitive to the empirical specifications than the estimated adjustment after the hazard shock.

The results of this paper are based on a sample of elderly people, the effect of mortality hazard shocks on consumption expenditures is likely to be considerably different at younger ages, when the mortality hazard is smaller.

	Mean	Median	Standard dev.	Observations
consumption (1000 EUR)	3.34	2.93	2.07	33,139
gross income (1000 EUR)	21.95	13.66	113.21	33,139
net worth (1000 EUR)	181.39	97.52	545.12	33,139
survival prob. (%)	60.51	60.00	28.67	30,148
age	66.71	67.00	7.65	33,139
female	0.58	1	0.49	33,139
has children	0.90	1	0.31	33,139
nr of siblings alive	2.32	2	2.13	31,951
new chronic disease	0.21	0	0.41	10,472
become ADL limited	0.06	0	0.23	10,472
differenced depression	-0.01	0	0.46	10,154
become single	0.02	0	0.15	10,472
sibling dies	0.12	0	0.23	10,472
all siblings dead by wave 1	0.06	0	0.24	10,472

Table 1: Descriptive statistics, first two waves of SHARE, retired respondents aged 50-80

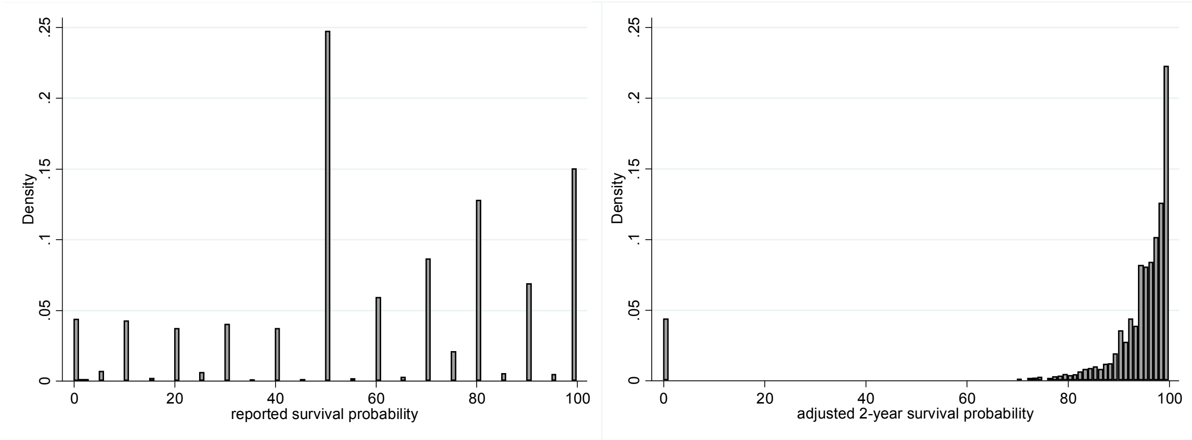

Figure 1: Histograms of the reported and adjusted survival probabilities, pooled data

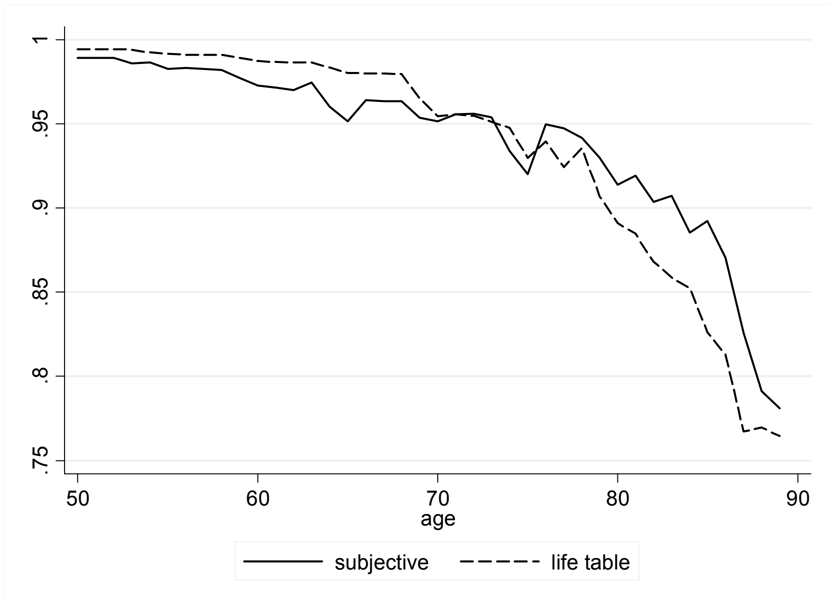

Figure 2: Median of subjective and life table 2-year survival probabilities as function of age

	diff. hazard	increasing hazard		hazard
sibling dies	0.008***	0.063***	all siblings dead	0.006**
	[3.01]	[3.90]		[2.13]
mother dies	0.004	0.063**	age mother	-0.000***
	[1.44]	[2.40]		[4.08]
father dies	0.005	0.097***	age father	-0.000*
	[1.45]	[2.62]		[1.80]
age	-0.005**	0.038***	age	0.003**
	[2.55]	[3.18]		[2.35]
age squared	0.000**	-0.000**	age squared	0.000
	[2.40]	[2.42]		[0.67]
female	-0.005***	-0.036***	female	-0.003**
	[3.57]	[3.62]		[2.47]
new cancer	0.022**	0.150**	had cancer	0.007**
	[2.24]	[2.02]		[2.40]
new heart attack	0.025*	0.173***	had heart attack	0.012***
	[1.89]	[2.65]		[5.66]
new stroke	-0.011	-0.084	had stroke	0.008**
	[0.68]	[0.78]		[1.98]
new fracture	0.011	0.087	had hip fracture	0.004
	[0.70]	[0.58]		[0.65]
new hypertension	0.005*	0.025	had hypertension	0.003**
	[1.81]	[1.55]		[1.99]
new high cholesterol	0.002	-0.028*	had high cholesterol	0.004**
	[0.68]	[1.65]		[2.38]
new diabetes	-0.012**	-0.047*	had diabetes	0.008***
	[2.53]	[1.81]		[3.18]
diff. ADL	0.001	0.065***	ADL	0.009***
	[0.21]	[2.82]		[3.35]
diff. depression	0.008***	0.065***	depression	0.013***
	[4.91]	[5.88]		[8.23]
become single	0.006	0.065*	single	0.002
	[1.08]	[1.82]		[1.17]
Constant	0.179***	-1.164***	Constant	-0.118***
	[2.83]	[2.94]		[2.74]
Observations	8,356	8,929	Observations	8,221
R-squared	0.01	0.04	R-squared	0.14

Absolute value of cluster robust t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2: OLS regression estimates of subjective hazard models, country dummies not reported

No controls

	Whole sample		Positive wealth	
	wave 1 hazard	diff. hazard	wave 1 hazard	diff. hazard
all siblings dead	0.019***	-0.004	0.020***	-0.005
	[6.16]	[1.22]	[5.97]	[1.31]
sibling dies	0.005***	0.009***	0.005***	0.009***
	[2.66]	[3.13]	[2.62]	[3.07]
F	21.48	5.87	20.27	5.82
Observations	8,447	8,447	8,009	8,009

Only age and age squared as controls

	Whole sample		Positive wealth	
	wave 1 hazard	diff. hazard	wave 1 hazard	diff. hazard
all siblings dead	0.010***	-0.004	0.010***	-0.005
	[3.16]	[1.25]	[3.22]	[1.34]
sibling dies	0.003	0.009***	0.000	0.009***
	[0.08]	[3.14]	[0.14]	[3.08]
F	5.00	5.98	5.20	5.94
Observations	8,447	8,447	8,009	8,009

With controls

	Whole sample		Positive wealth	
	wave 1 hazard	diff. hazard	wave 1 hazard	diff. hazard
all siblings dead	0.009***	-0.004	0.009***	-0.005
	[2.87]	[1.21]	[2.93]	[1.28]
sibling dies	0.001	0.008***	0.001	0.008***
	[0.43]	[2.89]	[0.44]	[2.84]
F	4.14	5.22	4.30	5.16
Observations	8,356	8,356	7,925	7,925

Absolute value of cluster robust t statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3: First stage estimation results of the consumption models, differenced hazard used as regressor

No controls

	Whole sample		Positive wealth	
	wave 1 hazard	hazard incr.	wave 1 hazard	hazard incr.
all siblings dead	0.020***	0.029	0.020***	0.026
	[6.31]	[1.31]	[6.21]	[1.16]
sibling dies	0.006***	0.103***	0.006***	0.098***
	[3.12]	[6.20]	[2.92]	[5.74]
F	23.53	19.59	22.31	16.74
Observations	8,763	8,763	8,289	8,289

Only age and age squared as controls

	Whole sample		Positive wealth	
	wave 1 hazard	hazard incr.	wave 1 hazard	hazard incr.
all siblings dead	0.009***	-0.011	0.010***	-0.012
	[3.10]	[0.48]	[3.27]	[0.51]
sibling dies	0.001	0.081***	0.000	0.077***
	[0.29]	[4.86]	[0.18]	[4.47]
F	4.80	12.23	5.34	10.44
Observations	8,763	8,763	8,289	8,289

With controls

	Whole sample		Positive wealth	
	wave 1 hazard	hazard incr.	wave 1 hazard	hazard incr.
all siblings dead	0.008***	-0.004	0.009***	-0.012
	[2.74]	[0.50]	[2.90]	[0.54]
sibling dies	0.001	0.070***	0.001	0.067***
	[0.44]	[4.19]	[0.35]	[3.88]
F	3.76	9.19	4.21	7.95
Observations	8,666	8,666	8,200	8,200

Absolute value of cluster robust t statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: First stage estimation results of the consumption models, binary indicator of increasing hazard used as regressor

No controls

	Whole sample		Positive wealth	
	IV	OLS	IV	OLS
differenced hazard	2.714	-0.065	5.952**	-0.066
	[1.06]	[0.39]	[2.24]	[0.39]
wave 1 hazard	-1.203	-0.424**	-1.066	-0.425
	[0.80]	[1.65]	[0.59]	[1.62]
R^2		0.001		0.001
p-value of Kleinbergen-Paap				
underidentification test	0.001		0.001	
observations	8,447	8,447	8,009	8,009

Only age and age squared as controls

	Whole sample		Positive wealth	
	IV	OLS	IV	OLS
differenced hazard	2.412	-0.043	5.673**	-0.050
	[0.87]	[0.26]	[2.00]	[0.30]
wave 1 hazard	-1.680	-0.383	-1.389	-0.397
	[0.48]	[1.43]	[0.35]	[1.45]
R^2		0.002		0.002
p-value of Kleinbergen-Paap				
underidentification test	0.002		0.002	
observations	8,447	8,447	8,009	8,009

With controls

	Whole sample		Positive wealth	
	IV	OLS	IV	OLS
differenced hazard	2.893	-0.032	6.301**	-0.056
	[0.96]	[0.20]	[1.97]	[0.34]
wave 1 hazard	-1.946	-0.319	-1.622	-0.331
	[0.51]	[1.18]	[0.37]	[1.19]
R^2		0.007		0.008
p-value of Kleinbergen-Paap				
underidentification test	0.005		0.004	
observations	8,356	8,356	7,925	7,925

Absolute value of cluster robust t statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Consumption model estimation results (second stage), differenced hazard used as regressor

No controls

	Whole sample		Positive wealth	
	IV	OLS	IV	OLS
hazard increase	0.295	-0.008	0.648**	0.007
	[1.06]	[0.48]	[2.25]	[0.44]
wave 1 hazard	-2.089	-0.343	-3.992*	-0.328
	[1.48]	[1.57]	[1.91]	[1.46]
R^2		0.001		0.001
p-value of Kleinbergen-Paap				
underidentification test	0.000		0.000	
observations	8,763	8,763	8,289	8,289

Only age and age squared as controls

	Whole sample		Positive wealth	
	IV	OLS	IV	OLS
hazard increase	0.246	-0.004	0.598*	0.009
	[0.81]	[0.27]	[1.89]	[0.61]
wave 1 hazard	-3.583	-0.287	-4.647	-0.281
	[0.96]	[1.23]	[1.20]	[1.17]
R^2		0.002		0.002
p-value of Kleinbergen-Paap				
underidentification test	0.002		0.001	
observations	8,763	8,763	8,289	8,289

With controls

	Whole sample		Positive wealth	
	IV	OLS	IV	OLS
hazard increase	0.307	-0.004	0.693*	0.007
	[0.85]	[0.25]	[1.79]	[0.47]
wave 1 hazard	-4.129	-0.221	-5.251	-0.209
	[0.97]	[0.94]	[1.16]	[0.85]
R^2		0.008		0.008
p-value of Kleinbergen-Paap				
underidentification test	0.006		0.004	
observations	8,666	8,666	8,200	8,200

Absolute value of cluster robust t statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Consumption model estimation results (second stage), binary indicator of increasing hazard used as regressor

Differenced hazard as regressor

	Whole sample	Positive wealth
diff. hazard	3.174	6.591**
	[1.16]	[2.35]
wave 1 hazard	0.324	1.230
	[0.10]	[0.32]
p-value of Kleinbergen-Paap		
underidentification test	0.002	0.002
observations	8,447	8,009

Increasing hazard indicator as regressor

	Whole sample	Positive wealth
hazard incr.	0.317	0.703**
	[1.09]	[2.33]
wave 1 hazard	-1.722	-2.357
	[0.49]	[0.64]
p-value of Kleinbergen-Paap		
underidentification test	0.002	0.001
observations	8,763	8,289

Absolute value of cluster robust t statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: IV estimation results, differenced logarithmic expenditure on food consumed at home as dependent variable

	Diff. hazard as regressor			Hazard incr. as regressor		
	diff. hazard	wave 1 hazard	obs.	hazard incr.	wave 1 hazard	obs.
2SLS	5.673***	-1.389	8,009	0.598*	-4.647	8,289
	[2.00]	[0.35]		[1.89]	[1.20]	
2SLS, 80+ included	0.832	-1.278	8,811	-0.030	-3.228	9,254
	[0.25]	[0.47]		[0.08]	[0.99]	
2SLS, 0% probability included	3.630**	-1.103	8,524	0.813**	-2.698	8,524
	[1.96]	[0.43]		[2.01]	[0.96]	
2SLS, positive financial wealth	6.838*	-1.782	6,015	0.793	-4.643	6,206
	[1.89]	[0.41]		[1.54]	[1.09]	
Cutoff: 1 %point decr. in survival probability				0.597*	-4.761	8,289
				[1.87]	[1.22]	
Cutoff: 2 %points decr. in survival probability				0.655*	-5.709	8,289
				[1.79]	[1.42]	
Fuller(1)	5.383**	-1.262	8,009	0.575*	-4.378	8,289
	[2.05]	[0.35]		[1.93]	[1.22]	
Fuller(4)	4.688**	-0.985	8,009	0.514**	-3.737	8,289
	[2.15]	[0.33]		[2.02]	[1.27]	
JIVE	8.538*	-2.710	8,009	0.709	-6.714	8,289
	[1.69]	[0.40]		[1.64]	[1.29]	
Age & death of parents as IV	4.125	1.372	7,717	0.280	0.821	7,982
	[0.84]	[0.57]		[1.06]	[0.68]	

Absolute value of cluster robust t statistics in brackets

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8: Robustness checks: hazard indicator coefficients in the consumption models (IV estimation, age and age squared controlled for)

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Appendix Consumption model IV estimation results, respondents with positive wealth

	With all controls		Age and age squared as controls	
diff. hazard	6.301**		5.673**	
	[1.97]		[2.00]	
hazard incr.		0.693*		0.598*
		[1.79]		[1.89]
wave 1 hazard	-1.622	-5.251	-1.389	-4.647
	[0.37]	[1.16]	[0.35]	[1.20]
age	0.058*	0.027	0.056**	0.029
	[1.84]	[0.92]	[2.00]	[1.07]
age squared	-0.000*	0.000	-0.000*	0.000
	[1.79]	[0.88]	[1.92]	[1.05]
mother dies	-0.005	-0.040		
	[0.10]	[0.72]		
father dies	-0.050	-0.097		
	[0.97]	[1.49]		
dln(income)	0.007	0.005		
	[1.35]	[0.83]		
female	0.019	-0.004		
	[0.74]	[0.18]		
has child	0.030	0.045		
	[0.90]	[1.24]		
new cancer	-0.463*	-0.336		
	[1.76]	[1.45]		
new heart attack	-0.171	-0.011		
	[1.22]	[0.08]		
new stroke	0.056	0.103		
	[0.41]	[0.83]		
new fracture	0.103	0.092		
	[0.38]	[0.26]		
new hypertension	-0.039	-0.028		
	[1.31]	[0.97]		
new high cholesterol	0.016	0.054*		
	[0.49]	[1.77]		
new diabetes	0.013	0.008		
	[0.16]	[0.11]		
diff. ADL	0.011	-0.026		
	[0.15]	[0.31]		
diff. depression	-0.041	-0.042		
	[1.27]	[1.37]		
become single	0.105	0.143**		
	[1.52]	[2.06]		
DE	-0.058	-0.007		
	[1.25]	[0.13]		
SE	-0.036	-0.008		
	[0.72]	[0.16]		
NL	-0.051	-0.039		
	[0.96]	[0.68]		
ES	-0.047	-0.044		
	[0.85]	[0.77]		
IT	-0.024	0.006		
	[0.51]	[0.13]		
FR	-0.006	0.027		
	[0.12]	[0.54]		
DK	-0.084	-0.058		
	[1.11]	[0.71]		
GR	0.032	0.075		
	[0.75]	[1.27]		
CH	-0.090	-0.091		
	[1.31]	[1.26]		
BE	-0.016	0.033		
	[0.33]	[0.61]		
Constant	-2.024*	-1.093	-1.895**	-1.097
	[1.84]	[1.05]	[1.98]	[1.13]
Observations	7,925	8,200	8,009	8,289

Absolute value of cluster robust t statistics in brackets
* significant at 10%; ** significant at 5%; *** significant at 1%