Subjective mortality hazard shocks and the adjustment of consumption expenditures
JOB MARKET PAPER

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Abstract

This paper analyzes the adjustment of consumption expenditures if the subjective mortality hazard increases after a shock. The life-cycle model with mortality risk implies an upward adjustment of consumption expenditures as a response to such a shock. I use data from the Survey of Health, Ageing and Retirement in Europe (SHARE) to test this implication. In each survey wave, the mortality hazard measure is based on the response to a question on subjective survival probability. The effect of the subjective hazard is identified by using the death of a sibling as instrument. The estimation results indicate that the consumption expenditures are adjusted upwards after the hazard shock among those who have positive wealth holdings and are thus not liquidity constrained.

Keywords: consumption decisions, subjective longevity, IV estimation
JEL classification: C26, D81, D91, J14

1 Introduction

Life expectancy at older ages is increasing. According to WHO statistics for the European region, life expectancy at age 65 in 1980 was 15.3 years on average for both genders. By 2008 this number had increased to 17.3.[1] It is not trivial how the increasing longevity affects the consumption and saving decisions of the elderly people. The first question is if people's longevity expectations correspond to the actuarial expected lifetime. The second question is how consumption and saving decisions react to the changing expected lifetime. In this paper I provide some answers to this second question by analyzing the adjustment of consumption expenditures of elderly people if the subjective longevity changes. In particular, I analyze if consumption is adjusted after a mortality hazard shock, and if this adjustment is in line with the implications of the life-cycle model.

The life-cycle model with mortality risk predicts that the ex ante effect of mortality hazard on the expected consumption dynamics is negative: those who have high hazard plan lower consumption level for the future, and consume more in the present. Another implication of the model is that increasing hazard affects the consumption level positively: an increase in the hazard implies that it is optimal to consume

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[1] These statistics are based on the WHO European health for all database.

more in the present, i.e. consumption should be adjusted. In this paper I test these two implications of the life-cycle model, focusing on the adjustment of consumption expenditures after an upwards hazard shock.

To my knowledge, this is the first paper to estimate the adjustment of consumption after a hazard shock on micro level data . For this purpose I use the first two waves of the Survey of Health, Ageing and Retirement in Europe (SHARE). The SHARE is a cross-national panel database of individuals aged 50 and above. The two key variables used are expenditure on food (as consumption measure), and the subjective survival probability to a given age. The latter variable is used to generate the subjective hazard indicators. I instrument the change in the hazard by the death of a sibling. The instrumenting strategy hinges on the observation that the death of a sibling influences the subjective survival probability, and such an event is not likely to have direct effect on the consumption expenditures of the elderly people. Instrumenting is needed since subjective hazard is endogenous in the consumption model due to the presence of measurement error and unobserved variables.

There is no consensus in the literature about the effect of increasing longevity on the aggregate consumption expenditures and savings. Skinner (1985a) shows on U.S. aggregate data that the life expectancy increased but the savings rates declined between 1970 and 1980. This finding contradicts the basic predictions of the life-cycle model. Skinner claims that bequest motives and life insurance can provide explanations for the decreasing saving rates. Bloom et al. (2002) also analyze the relationship between longevity and aggregate saving rates. They find some evidence from Asian and African countries that increasing life expectancy is associated with increasing savings rates. Li et al. (2007) derive that increasing longevity and rising old-age dependency rate affect the aggregate savings rate simultaneously and in the opposite direction. Their empirical results based on a panel of countries confirm that increasing longevity has positive effect on the saving rates, whereas higher old-age dependency rate has negative effect on that.

In this paper the individual level estimation results confirm the analyzed implications of the life-cycle model. Those who have positive wealth holdings are estimated to adjust their consumption expenditures upwards if the subjective mortality hazard increases. This effect is stronger if the oldest individuals are not included in the estimating sample, and also if those who are currently employed are excluded. The adjustment is estimated to take place through the expenditure on food consumed at home. The estimation results indicate that at age 60 if the expected remaining lifetime decreases by 4 years then that leads to around 330 EUR increase in the annual expenditure on food at the median. Assuming that the adjustment of consumption expenditures after increasing and decreasing mortality hazard is symmetric, the empirical results indicate that increasing perceived longevity leads to smaller consumption expenditures, hence to slower wealth decumulation. It has to be kept in mind that the evidence for the adjustment of consumption expenditures is based on a restricted sample: individuals aged between 50 and 80 are included in the sample, who have wealth holdings, and who live in some selected countries of Europe which exclude the post-socialist countries.

This paper is related to two strands of the literature: to empirical works which analyze the optimal 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.

A seminal article that introduces life-cycle models with mortality risk is of Yaari (1965). He derives the optimal consumption and saving dynamics under uncertain lifetime, with and without bequest motives and life insurance. Yaari shows that lifetime uncertainty can act analogously to increased impatience, but this may not hold if there are strong bequest motives or if wealth is restricted to be non-negative at the time of death. Hurd (1989) derives and estimates a life-cycle model with mortality risk and bequest motives. He assumes that there are borrowing constraints, and each individual receives fixed income flow. He finds based on data from the Longitudinal Retirement History Survey that bequest motives are weak. In addition, Hurd estimates that wealth is strongly (negatively) responsive to mortality rates. Using the Assets and Health Dynamics of the Oldest Old (AHEAD) data set, De Nardi et al. (2006) find that both differential life expectancy and expected medical expenditures have notable effect on asset accumulation. In their paper the authors compute survival probabilities from observed survival outcomes, and do not use self-reported survival probabilities.

Using subjective survival data in empirical economic analysis is a relatively new phenomenon. Survey data is known to be first used by Hamermesh (1985) to investigate the determinants of subjective survival probability, and he emphasizes the potential importance of subjective survival data in analyzing life-cycle behaviors. Based on observations from two questionnaires he shows that subjective life expectancy corresponds to actuarial life expectancy (demographic consistency) and to forecasted change in life expectancy (expectational consistency). In addition, he also documents that there is a huge reliance on parents' longevity, and the effects of personal behavior (e.g. smoking) on expectations are consistent with the evidence of their effect on longevity.

Hurd and McGarry (1993) analyze responses to subjective survival probability questions based on the Health and Retirement Study (HRS). They find that average reported probabilities are comparable to statistical life tables, reported survival probabilities to ages 75 and 85 are internally consistent for most of the respondents, and the subjective probabilities covary with observable risk factors in the same way as actual outcomes do. Using the HRS data, Smith et al. (2001) show that subjective survival probabilities can predict future mortality relatively well. Manski (2004) also argues for applying subjective probabilistic data in empirical work. He points out that the widespread usage of models assuming that people maximize their expected utility calls for the measurement of subjective expectations. Manski claims based on findings from large-scale surveys that respondents are willing to answer questions about subjective expectations, and the answers are generally reasonable and internally consistent. In addition, he provides some evidence that reported expectations and individual or mean realizations match up relatively well. Elder (2007) is more sceptical about the reliability of subjective survival data. Based on the HRS data he points out that reported survival probabilities to old ages are systematically upward biased relative to life table data, and the predictive validity of reported probabilities are also lower at older ages. Nevertheless, he finds some evidence that subjective longevity influences economic behavior: higher life expectancy is estimated to increase the tolerance for volatility in investment portfolio returns.

Subjective survival probabilities are used among others by Gan et al. (2004) and Salm (2006) in the empirical analysis of life-cycle models. Both papers use data from the Health and Retirement Study. The basic research question of Gan et al. (2004) is similar to that of Hurd (1989), which is the empirical analysis of bequest motives. However, Gan et al. also analyze the explanatory power of subjective survival probability on consumption and wealth trajectories. They compare the out-of-sample predictions of the life-cycle model using subjective and life table probabilities, and find that the subjective survival probabilities can explain the observed consumption and saving decisions better. Salm (2006) also investigates the effect of subjective life expectancy on the consumption and saving decisions of older people, his approach is estimating the Euler equation derived from the life-cycle model. He also finds that the explanatory power of subjective expectations on consumption dynamics is higher than that of the statistical life table data.

My paper contributes to the literature in estimating the effect of changing subjective mortality hazard on the consumption expenditures, and also in extending the analysis of consumption decisions to Europe. The Survey of Health, Ageing and Retirement in Europe data makes it possible to investigate how subjective life expectancy influences consumption expenditures of individuals aged 50 or over living in Europe. In this paper I identify the effect of a subjective hazard shock on consumption, and analyze if people adjust their consumption expenditures in line with the predictions of the life-cycle model. 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 are discussed in section 4, where I also discuss some potential caveats of the empirical model. A series of robustness checks are provided in section 5, and section 6 concludes.

2 The life-cycle model of consumption with uncertain lifetime

My purpose with the here presented life-cycle model is to derive implications for the empirical analysis: what factors influence the first differenced consumption, and what is the expected effect of increasing hazard. The modelling framework is related to life-cycle models with mortality risk, which are based on the article of Yaari (1965). Closely related models are developed also by Hurd (1989), Gan et al. (2004) and Salm (2006), who estimate life-cycle models with mortality risk and bequest motive. Salm (2006) also considers the effect of uncertain medical expenditures on consumption decisions.

The main deviation of the here presented life-cycle model from the cited models 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. First, I derive the Euler equation of consumption dynamics, then solve the model for the optimal consumption level, then analyze how changing mortality hazard affects the optimal consumption level in this life-cycle model. Some extensions of the model are discussed in section 5.3.

The maximization problem of individual i is:

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

C_{it} is consumption expenditure at time t, Y_i is time-invariant income, W_{it} is wealth, β is the discount factor, and R is one plus the interest rate. 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}. Consumption and income realizations take place at the beginning of each time period, whereas death can happen at the turning points to new periods. The budget constraint is imposed since it is assumed that there are no credit facilities, which can be a reasonable assumption for older individuals. The constant, annuity-type income is also realistic for older individuals who receive pension income. E_0 denotes expectations at time 0.

The only uncertainty in the model is mortality risk. I assume that individuals make their expectations on future survival using all the available information. They base their consumption decisions on these expectations. Using the law of iterated expectations, the expected value of future survival probabilities equals the current expectation of the survival probabilities, 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 maximization 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 $U(C_t) = C_t = 0$, thus only the $I_t = 1$ state matters, which occurs with probability $E_0(I_t)$.

The Bellman equation for the beginning of the tth period is:

$$V(W_{it}) = U(C^*_{it}) + E_t\left(I_{it+1}\right)\beta V(R(W_{it} - C^*_{it} + Y_i)), \tag{3}$$

where C^* denotes the optimal level of consumption, and the value function is conditional on survival to period t. The Lagrangian of the optimization problem under (1), using expression (2) is:

$$\Lambda_{it} = U(C_{it}) + E_t\left(I_{it+1}\right)\beta V(R(W_{it} - C_{it} + Y_i)) + \lambda_{it}(W_{it} - C_{it} + Y_i). \tag{4}$$

The first-order optimality conditions are:

$$\begin{aligned} \frac{\partial U(C_{it})}{\partial C_{it}} - E_t\left(I_{it+1}\right)\beta\frac{\partial V(W_{it+1})}{\partial W_{it+1}} - \lambda_{it} = 0 \\ W_{it} - C_{it} + Y_i \geq 0, \lambda_{it} \geq 0, \\ \lambda_{it}(W_{it} - C_{it} + Y_i) = 0. \end{aligned} \tag{5}$$

Differentiating equation (3) with respect to W_{it} gives:

$$\frac{\partial V(W_{it})}{\partial W_{it}} = \left[\frac{\partial U(C^*_{it})}{\partial C^*_{it}} - E_t\left(I_{it+1}\right)\beta R\frac{\partial V(W_{it+1})}{\partial W_{it+1}}\right]\frac{\partial C^*_{it}}{\partial W_{it}} + E_t\left(I_{it+1}\right)\beta R\frac{\partial V(W_{it+1})}{\partial W_{it+1}}. \tag{6}$$

Substituting the first condition under (5) into (6) gives:

$$\frac{\partial V(W_{it})}{\partial W_{it}} = \lambda_{it}\frac{\partial C^*_{it}}{\partial W_{it}} + E_t\left(I_{it+1}\right)\beta R\frac{\partial V(W_{it+1})}{\partial W_{it+1}}. \tag{7}$$

If the credit constraint is binding, then $\lambda_{it}\frac{\partial C^*_{it}}{\partial W_{it}} = \lambda_{it}\cdot 1 = \lambda_{it}$, otherwise $\lambda_{it}\frac{\partial C^*_{it}}{\partial W_{it}} = 0\cdot\frac{\partial C^*_{it}}{\partial W_{it}} = \lambda_{it}$. Therefore from (7) and (5):

$$\frac{\partial V(W_{it})}{\partial W_{it}} = \lambda_{it} + E_t\left(I_{it+1}\right)\beta R\frac{\partial V(W_{it+1})}{\partial W_{it+1}} = \frac{\partial U(C_{it})}{\partial C_{it}}. \tag{8}$$

Rewriting equation (8) gives the Euler equation:

$$\frac{\partial U(C_{it})}{\partial C_{it}} = E_t\left(I_{it+1}\right)\beta R\frac{\partial U(C_{it+1})}{\partial C_{it+1}} + \lambda_{it}. \tag{9}$$

Let's assume that the utility of current consumption is of the constant relative risk aversion (CRRA) form: $U(C_{it}) = \frac{C_{it}^{1-\gamma}}{1-\gamma}$, where $\gamma > 0$ is the coefficient of relative risk aversion, and its reciprocal is the intertemporal elasticity of substitution. Using this assumption, the Euler equation (9) can be rewritten:

$$C_{it}^{-\gamma} = E_t \left(I_{it+1}\right) \beta R C_{it+1}^{-\gamma} + \lambda_{it}. \tag{10}$$

Rearranging this expression, provided that the credit constraint is not binding, and using the law of iterated expectations:

$$\begin{aligned} \frac{C_{it+1}}{C_{it}} &= \left(E_t \left(I_{it+1}\right) \beta R\right)^{\frac{1}{\gamma}}, \\ C_{it} &= C_{i0} E_0(I_{it})^{\frac{1}{\gamma}} \left(\beta R\right)^{\frac{t}{\gamma}}. \end{aligned} \tag{11}$$

Equation (11) holds only if the wealth is not zero. If an individual has zero wealth level then 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. This result is derived also by Yaari (1965). A linearized version of equation (11) extended with the uncertainty of medical expenditures is estimated by Salm (2006). The Euler equation describes the expected consumption path, conditional on survival. However, the survival probability can change as the time elapses, thus the optimal consumption path can also change. 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 (objective) survival probability. This assumption is equivalent to the hazard-scaling approach of Gan et al. (2003), which is discussed in further details in section 3.2. Denote with η_{i0} the individual specific index of pessimism at time 0, and with S_t^{t+k} the life table survival probability from time t to time $t+k$. To simplify the 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 the subjective cumulative hazard of dying for individual i 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 (11) can be rewritten:

$$\ln C_{it+1} - \ln C_{it} = \frac{1}{\gamma} \ln\left(\beta R\right) - \frac{1}{\gamma} h_{it}^{t+1} = \frac{1}{\gamma} \ln\left(\beta R\right) + \frac{1}{\gamma} \eta_{i0} \ln S_t^{t+1}. \tag{12}$$

This is the Euler equation which describes the planned, ex ante dynamics of consumption based on the assumptions on the preferences and on the functional form of the subjective survival probability.

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 (before period T_i), and from that point on the Euler equation (11) does not hold. Thus the optimization problem can be solved only numerically, as done also by Gan et al. (2004) for a similar life-cycle model. 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 the 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

$$\sum_{t=0}^{T_i^*} \left(-\frac{C_{it}}{R^t} + \frac{Y_i}{R^t} \right) + W_{i0} = 0. \tag{13}$$

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 (11) into equation (13) and using the hazard-scaling assumption give the expression of optimal current consumption:

$$C_{i0} = \frac{W_{i0} + Y_i \frac{1-R^{T_i^*+1}}{R^{T_i^*} - R^{T_i^*+1}}}{\sum_{t=0}^{T_i^*} \frac{\left(S_0^t\right)^{\frac{\eta_{i0}}{\gamma}} (\beta R)^{\frac{t}{\gamma}}}{R^t}}. \tag{14}$$

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. The planned period one consumption level is $C_{i1} = C_{i0} \left(\left(S_0^1\right)^{\eta_{i0}} \beta R \right)^{\frac{1}{\gamma}}$.

My aim is to analyze the effect of unexpected changes in subjective hazard on consumption level. A hazard shock can be represented by an unexpected change in the pessimism index (η_i). In its simplest version, the life-cycle model predicts that the effect of a negative shock in subjective survival probability on the optimal consumption level is positive, and consequently, the effect of higher hazard is also positive. Assume that an upward shock affects the subjective hazard at the beginning of period one. This shock can be represented by increasing η_{i0} to η_{i1}. First I also assume that the time point of wealth depletion (T_i^*) 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 (14)) that the optimal consumption level at period one is

$$C_{i1} = RC_{i0} \frac{\sum_{t=0}^{T_i^*} \frac{\left(S_0^t\right)^{\frac{\eta_{i0}}{\gamma}} (\beta R)^{\frac{t}{\gamma}}}{R^t} - 1}{\sum_{t=1}^{T_i^*} \frac{\left(S_1^t\right)^{\frac{\eta_{i1}}{\gamma}} (\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}}}. \tag{15}$$

Using that $S_0^t = S_0^1 \cdot S_1^t$, it follows that the ex post difference between the consumption levels of the first two periods is

$$\ln C_{i1} - \ln C_{i0} = \frac{1}{\gamma} \ln (\beta R) - \frac{1}{\gamma} h_{i0}^1 + \ln \left(\sum_{t=1}^{T_i^*} \frac{\left(S_1^t\right)^{\frac{\eta_{i0}}{\gamma}} (\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}} \right) - \ln \left(\sum_{t=1}^{T_i^*} \frac{\left(S_1^t\right)^{\frac{\eta_{i1}}{\gamma}} (\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}} \right). \tag{16}$$

This expression shows that three mechanisms drive the consumption dynamics: first, the time preferences and the interest rate, second, the one period hazard which shows the effect of moving one period further in the lifetime, and finally, the hazard shock also influences the dynamics.

If the credit constraint is not binding then the differenced logarithmic consumption depends negatively

[2] The individual has two decison variables: C_{i0} and T_i^*. Based on the assumption of exact depletion the second identifying equation can be written down, and the tradeoff between the initial consumption level and the time of wealth depletion before T_i can be analyzed. $C_{iT_i^*} = C_{i0} \left(S_0^{T_i^*}\right)^{\frac{\eta_{i0}}{\gamma}} (\beta R)^{\frac{T_i^*}{\gamma}}$ from the Euler equation, and $C_{iT_i^*} = Y_i$ from the assumption of exact depletion at time $T_i^* < T_i$. Therefore $\frac{Y_i}{C_{i0}} = \left(S_0^{T_i^*}\right)^{\frac{\eta_{i0}}{\gamma}} (\beta R)^{\frac{T_i^*}{\gamma}}$, which shows that given income and initial consumption, T_i^* has to decrease if the mortality hazard increases (η_{i0} increases). In addition, if the life table survival probability were a power function of the one-period survival probability then the tradeoff between C_{i0} and T_i^* would be exponential.

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. This is a simplifying assumption. However, if T_i^* is large, and the hazard shock is moderate then equation (16) can still 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 (16) even smaller. Thus the expression under equation (16) can be considered as a lower bound of the ex post difference in the optimal logarithmic consumption expenditures.

I apply linear approximation of the differenced logarithmic term in equation (16) at η_{i0}:

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

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

$$=\left(\sum_{t=1}^{T_i^*}\frac{\left(S_1^t\right)^{\frac{\eta_{i0}}{\gamma}}(\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}}\right)^{-1}\left(\sum_{t=1}^{T_i^*}\frac{\left(S_1^t\right)^{\frac{\eta_{i0}}{\gamma}}(\beta R)^{\frac{t-1}{\gamma}}}{R^{t-1}}\left(-\eta_{i1}\ln S_1^t+\eta_{i0}\ln S_1^t\right)\right). \tag{17}$$

Since $-\eta_{i1}\ln S_1^t$ equals the cumulative hazard from period 1 to period t after the hazard shock, and $-\eta_{i0}\ln S_1^t$ equals the cumulative hazard before the hazard shock, substituting this approximation to equation (16) implies that the first differenced logarithmic consumption depends on the first differenced mortality hazard. Equation (17) also shows that the effect of the first differenced hazard is heterogenous, it depends on the initial survival probability

Motivated by the consumption model of equation (16), and using the approximation of equation (17), two versions of empirical consumption models will be estimated:

$$d\ln C_{i1} = \alpha_{01}+\alpha_{11}h_{i0}+\alpha_{21}dh_{i1}+u_{1i} \tag{18}$$

$$d\ln C_{i1} = \alpha_{02}+\alpha_{12}h_{i0}+\alpha_{22}H_i+u_{2i}. \tag{19}$$

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. As a simplification I neglect the heterogeneity in the effect of the indicators 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 (18) is based on the linear approximation of equation (16), whereas model (19) allows us 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 substitution, and also on changing expectations about future incomes. The adjustment of consumption to shifts in permanent income is analyzed 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 individual income is constant, but analyze the adjustment after changing subjective mortality hazard, which can be considered as adjustment after the arrival of new informations.

The result presented under equation (16) is an approximation, and cannot reveal the effect of a hazard shock on the optimal period of wealth depletion. If wealth is allowed to be depleted before time T_i then the exact solution of the consumption model can be found only numerically. Nevertheless, numerical results still indicate that the effect of an upward hazard shock on consumption expenditures is positive, and also that an upward hazard shock might decrease T_i^*. As a numerical example, using parameter values of $R = 1.05$, $\beta = 0.95$, $T = 10$, $\gamma = 2$, $Y = 100$, and $W_0 = 300$, Figure 1 illustrates how a change in mortality hazard affects the optimal consumption level and consumption path. In this example I assume constant one-period hazard. The ex ante consumption path is the solid line, whereas the ex post path is the dashed line. The positive hazard shock makes the path steeper, and the level of period one consumption is shifted upwards. At the same time, the wealth is depleted earlier, which also allows for increasing the consumption level at period one. This example reinforces that the life-cycle model implies a positive effect of increasing hazard on consumption, and also that the higher hazard level decreases the planned consumption level for the future.[3]

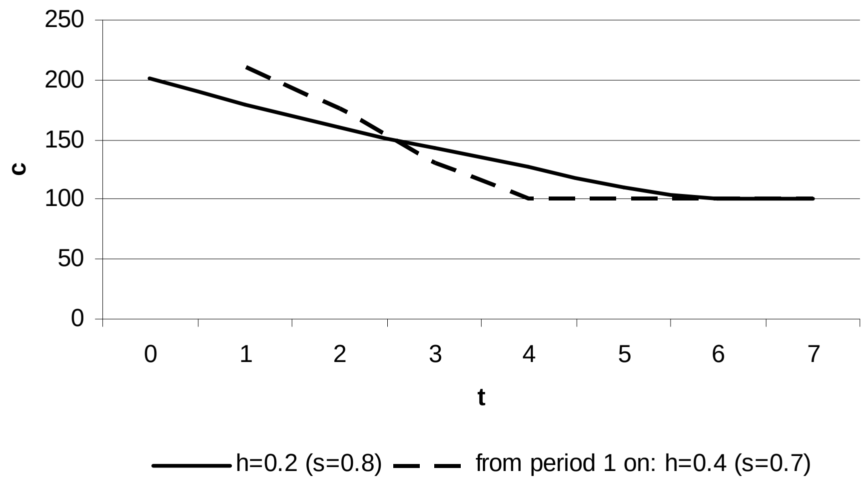

Figure 1: Numerical example: effect of a change in mortality hazard

[3]The upward shift in the optimal consumption level depends on the parameters in the model. The following table presents how much does the consumption level at period 1 increase if the one period hazard increases from 0.2 to 0.4 (the survival probability decreases from 0.8 to 0.7), and $R = 1.05, \beta = 0.95, T = 10, Y = 100$.

	$W = 100$	$W = 300$	$W = 1000$
$\gamma = 0.5$	0	33	107
$\gamma = 0.9$	9	85	130
$\gamma = 2$	26	32	72

These results clearly show that the effect of an upwards hazard shock on the optimal consumption level is positive, but this effect depends on the wealth level relative to income and on the preference parameters.

Holding the income fixed, if the wealth level is higher then the optimal consumption level is more sensitive to the hazard shock. On the other hand, the sensitivity is not a montone function of the coefficient of relative risk aversion.

3 Data

The empirical analysis is based on the first two waves of the Survey of Health, Ageing and Retirement in Europe.[4] The SHARE is a 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. It is a multidisciplinary database with a structure similar to the American Health and Retirement Study (HRS). The focus of the questionnaire is on the health, socioeconomic status, social and family networks of the respondents. I include those countries in the analysis for which both the first and second wave data are available. Therefore eleven countries can be included: Austria, Belgium, Denmark, France, Germany, Greece, Italy, the Netherlands, Spain, Sweden, and Switzerland. The number of individuals for whom the relevant variables are available in both waves is 16 thousand. I use unweighted data.

The consumption models are estimated on the subsample of individuals aged between 50 and 80 in the second wave of the survey. I exclude those individuals who are aged above 80 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. The question about subjective survival probability might be more difficult for them to answer, the higher nonresponse rate also reflects this problem. The following statistics and results refer to the restricted estimation sample, however, in section 5.1 I present a robustness check with respect to the age restriction.

3.1 Variables used

Table 1 includes some descriptive statistics of the variables used in the empirical analysis. These are the measures of consumption expenditures, and such variables which can have influencing effect on the difference in consumption expenditures between the two waves. The financial variables (consumption, income, and wealth) 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. Using the average of the imputed values is a simplification which can cause some downward bias in the standard error estimates. The household level consumption, income and wealth measures are divided by the household size, so that these can represent individual amounts.

Consumption is measured by annual expenditure on food at home and outside home.[5] 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 (2.4% out of those second wave respondents for whom the differenced consumption is not missing). Measuring consumption by expenditures on food is a data limitation since the SHARE does not ask about overall or other categories of consumption expenditures. Based on Eurostat statistics for year 2006 the expenditure on food is around 13% of overall household expenditures in the European Union. Nevertheless, the 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

[4] 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).

[5] 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.

	Mean	Median	Standard dev.
consumption (1000 EUR)	2.96	2.56	1.90
income (1000 EUR)	21.48	13.37	98.61
net worth (1000 EUR)	180.45	88.61	535.57
ln(consumption)	7.84	7.85	0.62
dln(consumption)	-0.02	-0.02	0.66
survival prob. (%)	64.12	70.00	27.61
age	63.03	62.00	8.39
female	0.54	1	0.50
new chronic disease	0.13	0	0.33
become ADL limited	0.04	0	0.21
d(depression)	-0.02	0	0.45
exit employment	0.05	0	0.21
become single	0.01	0	0.12

Table 1: Descriptive statistics, first two waves of SHARE

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. As an extension, in section 4.5 I analyze separately the adjustment of expenditures on food consumed at and outside home after a hazard shock.

Income is measured as total gross income, which includes income from employment, pension, regular transfers, capital asset incomes and received rent payments as well. The life-cycle model presented in section 2 is based on the assumption of time-invariant income, although the observed nominal income varies between the two waves. However, 72% of the individuals in the estimation sample receive pension income, which can be considered as annuity. Among those single individuals who receive pension, the mean ratio of pension income to total income is 80%, and the median is 95%. Thus the majority of the sample consists of pensioners, for whom the dominant source of income is the pension income.

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 and high blood cholesterol since the first interview. Only about 13% of the respondents report being diagnosed with any of these conditions since the first interview. Two additional health measures are used, which are indicators of reporting limitations with activities of daily living (ADL), and whether the respondent suffers from depression.[6] 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. Exiting employment is also a binary variable which equals one if a respondent was employed or self-employed in wave 1 but not in wave 2.

The variables of central interest are the subjective survival probability and mortality hazard generated from the reported probability. As I discuss in section 3.2, not the reported survival probability but an adjusted value is used in the estimations. 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 $75 - 110$). This question is included in the expectations section of the questionnaire. The introduction to this block is a warm-up question about the chances for sunny weather on the following day. This might help respondents in answering probabilistic questions. The item nonresponse

[6] The SHARE data includes a binary indicator of depression, based on the EURO-D scale of depression.

rate to the survival probability question is around 8% in both waves.

3.2 Measuring subjective hazard

Using the level or the change of reported survival probability in the empirical models could lead to unreliable results. The main reason is that due to survey design the difference between the target age and the current age of the respondents varies across ages. The reported survival probability can change not only if the subjective life expectancy changes, but also if the target age in the probability question changes. Therefore the reported probabilities should be adjusted. In addition, an important problem related to probabilistic survey questions is the high proportion of focal responses (0, 50 or 100 percentage reported probabilities).

One potential approach for adjusting the reported probabilities is suggested by Hill et al. (2004). The authors apply the so-called modal response hypothesis, i.e. the respondents are assumed to report the probability which is the most likely among the possible probabilities. They show that focal responses become more likely with increasing uncertainty. Using cross-sectional HRS data they apply maximum likelihood estimation to estimate the distribution of beliefs, conditional on a set of individual characteristics.

A different approach is suggested by Gan et al. (2003). They derive a "hazard-scaling" and alternatively an "age-scaling" index, which is used to derive the individual subjective survival curves. In addition, due to the large proportion of focal responses they apply a Bayesian approach to obtain the posterior density of the underlying subjective survival probability. The authors make use of the observed death records in the HRS data when estimating the expected value of the posterior subjective survival probability. This approach of probability adjustment is applied by Gan et al. (2004) and Salm (2006) when analyzing consumption and wealth dynamics.

I apply a similar adjustment method as Salm (2006) does. The reported probability is adjusted so that for each individual it represents the subjective probability of living at least two years more. I do not make any further adjustment in the reported probability, assuming that the reported probability includes all the available information about the subjective survival beliefs.

The adjustment procedure is based on the hazard-scaling approach of Gan et al. (2003), which also corresponds to the assumptions made in the life-cycle model of section 2. It is assumed that the individual hazard function equals the life table hazard function multiplied by a constant. The first step is to derive an individual specific index of pessimism:

$$\eta_i = \frac{\ln \tilde{s}_{it}^{t+a}}{\ln S_t^{t+a}}, \tag{20}$$

where the notations follow those of section 2, t is the current age, and $t+a$ is the target age, and $\tilde{s}$ is the reported survival probability. The WHO life tables for year 2006 are used, which are gender and country specific life tables.[7] 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.

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

$$s_{it}^{t+2} = \left(S_{it}^{t+2}\right)^{\eta_i}, \tag{21}$$

and the 2-year cumulative hazard is

$$h_{it}^{t+2} = -\eta_i \ln S_{it}^{t+2}. \tag{22}$$

[7] The source of the life tables is: http://apps.who.int/whosis/database/life_tables/life_tables.cfm

The 2-year difference between the target and current age is specified because on average two years elapse between the two observations of consumption expenditures. The Euler equation (equation (12)) implies that the estimated intertemporal elasticity of substitution can be obtained if the two-year hazard is included in the model. The mean of the difference between the current and target age in the survey is 15.8.

The pessimism index cannot be calculated for those who report 0% (almost 5% of the respondents of the estimation sample report 0% survival probability in either the first or second wave survey). Therefore the adjusted mortality hazard is missing for them. When estimating the consumption models I exclude those respondents for whom the subjective hazard is missing, but in section 5.1 I analyze how sensitive are the results to assuming that the 0% reported probability is due to rounding, and the real subjective survival probability is 0.5%.

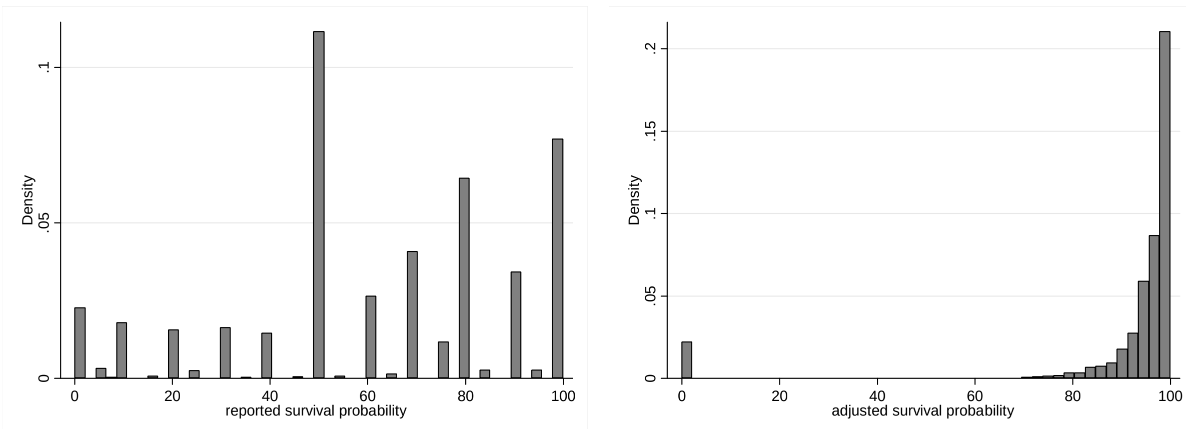

Figure 2: Histograms of the reported and adjusted survival probabilities, pooled data

The correlation between the reported and generated survival probability is 0.63 (if the zero reported probabilities are excluded then it is 0.80). The histograms of these two variables are presented in Figure 2, 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, which is a shorter period than the average difference between the target and current age in the questionnaire. The spikes above 0% and below 100% survival probability disappear due to the adjustment procedure.[8] The histogram of the reported survival probabilities clearly show the problem of focal responses, which indicates measurement error.

A comparison between the life table and reported subjective survival probabilities is provided by Figure 3. The figure depicts the median of the subjective and life table 2-year survival probabilities by age, up to age 90. The life table probabilities are based on the WHO data. The subjective survival probabilities are based on the above described adjustment procedure. The figure is comparable to the figures reported by Borsch-Supan et al. (2005), p. 336. 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, there is some evidence that people overestimate their survival probability at older ages, whereas their is slight underestimation at younger ages.

[8]The spike at 100% survival probability remains, which is a consequence of the adjustment procedure. The pessimism index (η) equals zero for those who report 100% survival probability, thus the adjusted survival probability (s) also equals 100%.

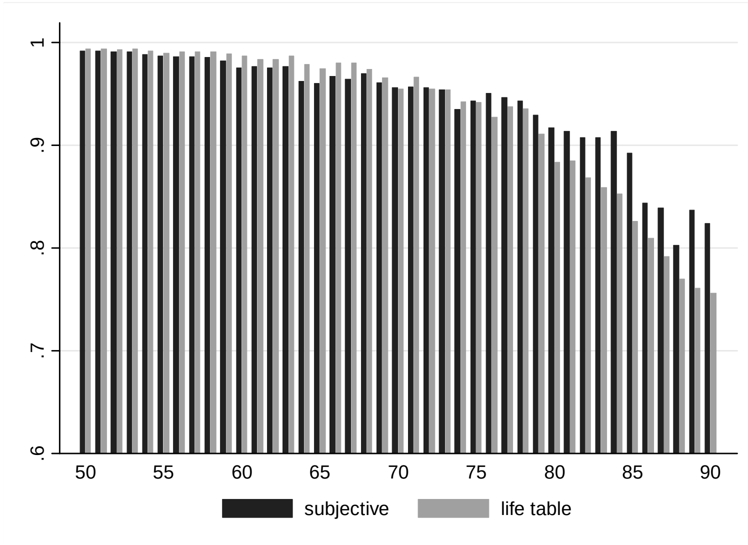

Figure 3: Median of subjective and life table 2-year survival probabilities as function of age

In Table 2 I present the estimated coefficients of three OLS models. These models show how do the subjective hazard indicators correspond to the death of relatives, to the parents' longevity, and to other individual specific characteristics. In the first part of the table 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 subjective survival probability between the first and second waves of the survey. There is one outlier value with hazard increase above 5, this observation is excluded from the estimations. The binary indicator of increasing hazard equals one for 27% of the respondents in the estimation sample. 1.5 percentage points decrease in the two-year survival probability is on average similar to 10 percentage points decrease in the ten-year survival probability. 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.

The included regressors are variables that might influence the hazard indicators. 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. These indicators will serve as instruments in the consumption model. The death of a sibling between the two survey waves is used as instrument for increasing subjective hazard. For 10% 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.[9] The level of first wave hazard is regressed among others on a binary variable which equals one if the respondents has no siblings alive in wave one, but reports that he had siblings before (5% of the respondents in the estimation sample).

Based on these estimations the respondents update their survival probabilities if a sibling dies, the death of a sibling has significantly positive effect on the subjective mortality hazard. This effect is stronger if the binary indicator of increasing hazard is used. The death of a parent has also positive effect on the subjective hazard, but this effect is weaker. Only few of the indicators of newly diagnosed diseases have significant

[9] For 751 respondents the observed change in the number of siblings alive between the two waves is positive, which indicates measurement error in this variable. For 167 respondents the observed decrease is more than three.

	dhazard	increasing hazard		hazard
sibling dies	0.003*	0.048***	all sibling died	0.005**
	[1.83]	[3.66]		[2.30]
mother dies	0.002	0.037**	age mother	-0.000***
	[1.15]	[2.23]		[5.76]
father dies	0.002	0.043**	age father	-0.000**
	[1.19]	[2.09]		[2.21]
age	-0.000***	0.011***	age	0.002***
	[3.51]	[22.16]		[30.63]
male or female	-0.003***	-0.014*	male or female	-0.003***
	[3.45]	[1.92]		[3.80]
new cancer	0.014**	0.144**	had cancer	0.006***
	[2.08]	[2.25]		[2.84]
new heart attack	0.017*	0.119**	had heart attack	0.011***
	[1.82]	[2.06]		[6.89]
new stroke	-0.013	-0.128	had stroke	0.008**
	[1.12]	[1.42]		[2.52]
new fracture	-0.007	0.037	had hip fracture	0.005
	[0.39]	[0.27]		[0.94]
new hypertension	0.004*	0.024*	had hypertension	0.002**
	[1.85]	[1.89]		[2.46]
new high cholesterol	-0.001	-0.006	had high cholesterol	0.002**
	[0.61]	[0.45]		[2.39]
new diabetes	-0.008**	-0.030	had diabetes	0.006***
	[2.43]	[1.41]		[3.20]
dADL	0.008	0.088***	ADL	0.010***
	[1.47]	[4.34]		[4.32]
ddepression	0.007***	0.043***	depression	0.010***
	[4.91]	[5.14]		[9.71]
exit emp	0.001	0.038***	employed	-0.004***
	[0.98]	[2.65]		[4.71]
become single	0.003	0.053**	single	0.003***
	[0.84]	[1.96]		[2.80]
Constant	0.017***	-0.400***	Constant	-0.073***
	[3.72]	[11.29]		[13.82]
Observations	13,603	14,319	Observations	12,977

Absolute value of cluster robust t statistics in brackets

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

Table 2: OLS models of changing subjective mortality hazard and hazard level, country dummies not reported

effect on the hazard, which might be due to the few observations on new diagnosis.

The estimation results indicate that if the respondent had siblings but all of them are dead then the subjective mortality hazard is significantly higher. The magnitude of this effect is close to the positive effect the death of a sibling between the two survey waves has on the hazard. The age or age of death of a parent has also significant effect on the hazard, this effect is negative. The health indicators have the expected effect on subjective hazard: having been diagnosed with chronic health conditions, having ADL limitations or symptoms of depression increase the subjective mortality hazard, and this effect is significant for most of the health problems.

The presented results are in line with the findings of Hamermesh (1985) and Hurd and McGarry (1993): the observed health problems have positive effect on the hazard measure, which indicates that this is a reliable measure of the subjective hazard. At the same time, the subjective hazard is estimated to depend on the longevity of the relatives.

4 Estimation results

4.1 Empirical specification

In this paper I analyze how the hazard level and increasing mortality hazard affect the consumption expenditures of older individuals. Using the first two waves of the SHARE data this effect can be analyzed by estimating cross-sectional regressions of the first differenced consumption on mortality hazard indicators. The estimated models are based on equations (18) and (19). 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. Thus there are two specifications of the empirical consumption model:

$$d \ln C_{i1} = \alpha_{01} + \alpha_{11} h_{i0} + \alpha_{21} dh_{i1} + X_i \alpha_{31} + e_{1i} \tag{23}$$

$$d \ln C_{i1} = \alpha_{02} + \alpha_{12} h_{i0} + \alpha_{22} H_i + X_i \alpha_{32} + e_{2i}. \tag{24}$$

The X_i vector includes variables that can indicate individual-specific preferences or changes in preferences. These variables are age, gender, having children, dummies of being diagnosed with chronic diseases since the first wave[10], ADL limitation and first differenced binary indicator of depression, becoming single, quitting employment, and country dummies as controls for preferences and country-specific factors in consumption expenditures. I include the death of a parent also as an explanatory variable since that is likely to influence the consumption expenditures e.g. through bequests or through the costs associated with the funeral. The first differenced logarithmic income is also included in X_i, allowing income shocks to influence consumption expenditures. I estimate two versions of the model: first, only the hazard indicators are included as regressors, second, the additional controls (vector X_i) are also included in the model.

The subjective survival probability is measured with error, which is also reflected by the large fraction of focal responses. As a consequence, the hazard level (h_{i0}), the differenced hazard (dh_{i1}) and the binary indicator of increasing hazard (H_i) are also measured with error. If the measurement errors in the differenced hazard and lagged hazard are correlated with the observed hazard values then the OLS estimator is biased (classical measurement error). This is likely to be the case since negative measurement error can

[10] The following seven diseases are considered: heart attack, stroke, cancer, hip fracture, high blood pressure, high blood cholesterol, diabetes.

cause low observed hazard rates, therefore the differenced observed hazard and its measurement error are also correlated. In addition, unobserved changes in the health status can affect not only the consumption dynamics but also the reported survival probability, making the first differenced hazard endogenous in the model. These endogeneity concerns call for the application of the method of instrumental variables.

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. Some details on this indicator is given in section 3.2. Hamermesh (1985) already pointed out the strong reliance of subjective survival probability on forebears' longevity. However, there are multiple reasons why I use only the death of a sibling as an instrument of changing mortality hazard. Firstly, it affects the subjective hazard and can be a valid instrument, as the death of a sibling is unlikely to have direct effect on food consumption expenditures. The latter might not be true for the parents or the children of the respondent. Secondly, the respondents are aged 50 or above, for whom the death of a parent is likely to affect the subjective mortality hazard to a less extent than for younger individuals. Including irrelevant instruments would exacerbate the problem of weak instruments. Table 2 indeed shows that the effect of the death of a parent on the 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. Section 3.2 provides some details on this indicator and on its effect on the reported hazard. Bloom et al. (2006) apply a different instrumenting strategy: they instrument the subjective survival probability with the age or age of death of the parents, using the HRS data. If a parent died at young ages then that might influence the further consumption path of the child. Also the parents and their children might share some consumption expenditures, and their death is more likely to directly affect the consumption expenditures, thus the age or age of death of the parents might not be valid instrument in the consumption model. Nevertheless, I make a robustness check in section 5.2 with respect to this alternative instrumenting strategy.

In Table 3 I present the coefficients of the instruments from the first stage of the consumption model. This table refers to the specification under equation (23), where the differenced hazard is a regressor. There are four specifications according to the inclusion of the additional controls (X vector), and to the estimation sample. First I estimate the model for the whole population aged at least 50 but not more than 80, then I restrict this estimation sample to those who have positive wealth holdings, according to the net worth indicator. I present also the value of the F-test, where the null hypothesis is that the two instruments are jointly insignificant.

Table 4 is analogous to Table 3, the difference is that Table 4 presents the selected first stage coefficients from the model of equation (24). Here the binary indicator of increasing hazard is included in the consumption model.

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. On the other hand, the instruments are weaker if additional controls are included in the consumption models. The F statistics indicate that the instruments are the strongest if the binary indicator of increasing hazard is used as regressor, but the additional control variables are not included in the model (upper part of Table 4).

No controls

	Whole sample		Positive W	
	l.hazard	dhazard	l.hazard	dhazard
all sibling died	0.021***	-0.006**	0.022***	-0.007**
	[8.58]	[2.30]	[8.41]	[2.35]
sibling dies	0.007***	0.004**	0.007***	0.004**
	[5.05]	[2.09]	[4.90]	[2.10]
F	47.60	5.06	45.47	5.19

With controls

	Whole sample		Positive W	
	l.hazard	dhazard	l.hazard	dhazard
all sibling died	0.007***	-0.005*	0.008***	-0.005*
	[3.01]	[1.88]	[3.13]	[1.94]
sibling dies	0.001	0.004**	0.000	0.004**
	[0.50]	[2.24]	[0.37]	[2.22]
F	4.59	4.65	4.91	4.74

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

Table 3: First stage estimation results, differenced hazard as regressor in the consumption model

No controls

	Whole sample		Positive W	
	l.hazard	hazard incr.	l.hazard	hazard incr.
all sibling died	0.022***	0.061***	0.023***	0.060***
	[8.82]	[3.23]	[8.69]	[3.09]
sibling dies	0.008***	0.099***	0.008***	0.098***
	[5.62]	[7.32]	[5.39]	[7.04]
F	52.32	30.61	49.94	28.28

With controls

	Whole sample		Positive W	
	l.hazard	hazard incr.	l.hazard	hazard incr.
all sibling died	0.007***	-0.005	0.008***	-0.006
	[2.86]	[0.25]	[3.08]	[0.32]
sibling dies	0.001	0.054***	0.000	0.053***
	[0.52]	[4.00]	[0.30]	[3.77]
F	4.14	8.15	4.73	7.29

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

Table 4: First stage estimation results, increasing hazard indicator as regressor in the consumption model

4.3 Second stage results

Estimating the consumption models of equations (23) and (24) can reveal how the consumption level is adjusted after hazard shocks. At the same time, the ex ante effect of subjective mortality hazard on the consumption dynamics is also estimated. If the presented life-cycle model is realistic than the effect of first wave hazard on differenced consumption is negative, whereas the effect of the indicator of increasing hazard is positive. A related model of consumption level is estimated by Skinner (1985b). Using cross sectional data from the Consumption and Expenditure Survey and using race- and occupation-specific life tables, he regresses the logarithmic consumption on the logarithm of mortality rate. Skinner estimates positive effect of mortality on consumption.

As discussed under the first stage results, I estimate the model 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. I also reestimate the models with including additional control variables that might affect the consumption dynamics. Due to the measurement error in the hazard indicators and to the potential influence of unobservables, I apply the method of IV estimation with the death of a sibling between the two waves, and the death of all siblings before wave as instruments. However, for the sake of comparison I also reestimate the models with OLS.

The models are estimated for individuals aged between 50 and 80, but in section 5.1 I analyze the robustness of the results with respect to including the oldest respondents in the estimation sample. Zero reported survival probabilities are excluded from the estimations. All the households, and not only the single households are included in the estimation sample. Although the modelling assumption that consumption expenditures are based on individual decisions can be more reliable for single individuals, restricting the sample to singles would necessitate the exclusion of almost 80% of the observations and thus small sample problems would arise.

In the first set of specifications I include the differenced hazard as a measure of increasing hazard (equation 23)). The estimated coefficients of interest are presented in Table 5, the full set of the estimated coefficients if additional controls are included are reported in Appendix A. The estimations are repeated with the difference that not the change in hazard is included as a regressor, but a dummy variable indicating if a big increase is recorded in the subjective mortality hazard (equation (24)). The increase in hazard is defined to be big if there is at least 1.5 percentage points decrease in the adjusted survival probability between the two waves. The binary variable is zero if no such decrease is recorded, but the survival probability is not missing. The estimated coefficients based on this specification are reported in Table 6, the detailed estimation results are reported in Appendix B.

No controls

	Whole sample		Positive W	
	IV	OLS	IV	OLS
dhazard	4.870	-0.171	7.909**	-0.183
	[1.32]	[1.31]	[2.08]	[1.36]
l.hazard	-0.212	-0.555**	0.382	-0.574**
	[0.16]	[2.41]	[0.26]	[2.44]

With controls

	Whole sample		Positive W	
	IV	OLS	IV	OLS
dhazard	5.429	-0.147	8.932*	-0.173
	[1.20]	[1.17]	[1.82]	[1.35]
l.hazard	0.003	-0.468*	1.553	-0.495*
	[0.00]	[1.83]	[0.28]	[1.86]

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

Table 5: Consumption model estimation results, differenced hazard as regressor

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. On the other hand, the effect of lagged hazard is significantly negative only under the OLS specifications. This effect is insignificant in the IV models, and even positive but with large standard error if the sample is restricted to those with positive wealth holdings. Based on the IV estimation results, the partial effect of increasing hazard on consumption expenditures is positive, but this effect is significant only for those who are not credit constrained. This is what the life cycle model predicts: if someone lives from the annuity type income then the consumption is unaffected by the subjective mortality hazard. These results suggest that the ex post effect of subjective hazard on consumption expenditures is stronger than the ex ante effect of subjective hazard.

Since the instruments are considered to be exogenous, omitting other control variables does not cause bias in the IV estimates. Indeed, the point estimates of the differenced hazard coefficient are affected only slightly by the inclusion of the additional controls. However, the point estimate of the first wave hazard coefficient is more sensitive to extending the model.

No controls

	Whole sample		Positive W	
	IV	OLS	IV	OLS
hazard incr.	0.382	-0.011	0.612**	-0.008
	[1.30]	[0.87]	[2.10]	[0.64]
l.hazard	-3.154*	-0.425**	-4.115**	-0.431**
	[1.71]	[2.09]	[2.13]	[2.05]

With controls

	Whole sample		Positive W	
	IV	OLS	IV	OLS
hazard incr.	0.401	-0.007	0.651	-0.007
	[1.03]	[0.57]	[1.60]	[0.53]
l.hazard	-5.089	-0.306	-5.818	-0.318
	[1.11]	[1.33]	[1.26]	[1.32]

Absolute value of cluster robust t statistics in brackets

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

Table 6: Consumption model estimation results, increasing hazard as regressor

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 if the sample of individuals with positive wealth is used (Table 6). On the other hand, the coefficient of lagged hazard is negative both under the OLS and IV estimates, but its magnitude and significance are sensitive to the estimation method and to the inclusion of additional controls. The coefficient of the lagged hazard is the negative of the inverse of the coefficient of relative risk aversion. The OLS estimates indicate a much higher risk aversion coefficient (around $2-3$) than the IV estimates do (around $0.2-0.3$).

Based on the presented results it is clear that using instrumental variables when estimating the effect of subjective hazard on consumption is important. It affects not only the size of the estimated coefficients but in some cases also the sign of those. The absolute value of the IV estimates are always above the OLS estimates. The preferred specifications are the ones without the inclusion of additional controls, estimated with IV method on the subsample of individuals with positive wealth. These specifications indicate that the consumption path depends on the hazard shocks. The positive sign of this effect correspond to the predictions of the life-cycle model. The coefficient of the lagged hazard is sensitive to the included indicator of changing hazard. There is strong negative correlation between the lagged hazard and the differenced hazard (the correlation coefficient is -0.5), which can cause unreliable coefficient estimates, and also the problem of weak instruments is exacerbated by it. On the other hand, the correlation coefficient between the lagged hazard and the binary indicator of increasing hazard is weaker (-0.1), therefore the estimation results are more reliable if the binary indicator is included in the model. However, it might be that in this specification the negative coefficient of the lagged hazard is due to the positive effect of differenced hazard, which cannot be fully captured by the binary indicator of increasing hazard.

The magnitude of the estimated effect of a hazard shock is not negligible. Based on the logarithmic transformation, increasing the mortality hazard by one is equivalent to decreasing the two-year survival probability for example from 80% to 30% or from 50% to 20%. On average, such a change in mortality hazard has around ten times larger effect on the consumption expenditures than a 1.5 percentage points or higher decrease in the 2-year survival probability. The estimated positive partial effect of increasing hazard on logarithmic consumption is around the standard deviation of the logarithmic consumption level in the second wave sample. The effects are nonlinear. Around the median expenditure, if the logarithmic value of food consumption expenditures decreases or increases by 0.6 due to a shock in mortality hazard then that is equivalent to $100 - 180$ EUR change in the individual monthly expenditures.[11]

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.[12] Based on the results presented in Table 5, such a decrease in the expected longevity leads to around 330 EUR increase in the annual expenditure on food at the median, ceteris paribus.

4.4 Euler equation

The standard approach in the empirical analysis of consumption is estimating the Euler equation based on the life-cycle model of consumption. An overview of this approach is provided by Attanasio and Weber (2010). Estimating the Euler equation makes possible to test the validity of the life-cycle model, and to estimate the parameters of the utility function. Although in this paper my focus is on the effect of mortality hazard shocks on consumption expenditures, I present here the results of the Euler equation estimation. Since both the differenced hazard and the binary indicator of increasing hazard are correlated with the first wave hazard, including only the first wave hazard as regressor leads to omitted variable bias. Instrumenting the lagged hazard with the indicator of the death of all siblings before wave one does not solve this problem because this instrument is also a predictor of the changing hazard (as presented in Tables 3 and 4), so the ex ante effect of subjective hazard cannot be separately identified. Nevertheless, the Euler equation estimation results can be compared to the estimation results presented in section 4.3.

The life-cycle model implies that the growth rate of consumption expenditures is lower if the mortality hazard is higher. This implication can be tested by estimating the following equation:

$$d \ln C_{i1} = \alpha_0 + \alpha_1 h_{i0} + X_i \alpha_2 + e_i. \tag{25}$$

This model is analogous to equations (23) and (24), but the differenced hazard or the indicator of increasing

[11] The mean of the differenced hazard in the estimating sample is 0.017, and the median is 0.006. Thus for the majority of the observations the predicted ceteris paribus increase in consumption expenditures due to the changing hazard is moderate, based on the estimation results presented in Table 5.

[12] 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.

hazard is excluded. The adjusted subjective cumulative hazard of dying in the next two years at wave one is used as regressor (h_{i0}). The X_i vector includes the same variables as earlier. Again, I apply both the IV and OLS estimation method. Instrumenting is needed because of the likely presence of measurement error and unobserved variables, the instrument is the binary indicator which equals one if the respondent had siblings but none of the siblings are alive in wave one. The model is estimated with and without the inclusion of the additional control variables, and on two samples: the whole estimation sample and the sample of individuals with positive wealth holdings. The estimated coefficients of the lagged hazard indicator are reported in Table 7.

No controls

	Whole sample		Positive W	
	IV	OLS	IV	OLS
l.hazard	-1.966	-0.407**	-2.544**	-0.402**
	[1.62]	[2.12]	[2.05]	[2.03]

With controls

	Whole sample		Positive W	
	IV	OLS	IV	OLS
l.hazard	-5.090	-0.254	-6.756	-0.275
	[1.19]	[1.17]	[1.57]	[1.22]

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

Table 7: Euler equation estimation results

Based on the Euler equation, the presented coefficients equal the negative inverse of the coefficient of relative risk aversion (which is the negative intertemporal elasticity of substitution). However, reliable estimation of the parameter of the utility function would require longer time-series than two years. Nevertheless, the results show that the estimated effect of subjective mortality hazard on consumption expenditure dynamics is significantly negative under the OLS estimations, and also under the IV estimation if no additional controls are included in the model and the sample is restricted to those with positive wealth. This negative effect is larger in absolute value under the IV estimations. The negative estimated effect is in line with the predictions of the life-cycle model.

The OLS results change moderately with the inclusion of additional controls, which it is not true for the IV estimates, where the sensitivity of the estimated hazard coefficient can be due to the problem of weak instruments. If additional controls are included then the hazard coefficient becomes insignificant but larger in absolute value. The estimated coefficients indicate that the effect of the lagged value of subjective hazard on the differenced consumption is weaker for those who have no wealth holdings. This is also in line with the life-cycle model, since if the credit constraint is binding then the Euler equation does not hold.

The estimated effect of the lagged hazard is comparable to the estimates if the binary indicator of increasing hazard is included in the model (Table 6). The intertemporal elasticity of substitution seems to be underestimated if the increasing hazard measure is omitted from the model. On the other hand, these results are different from the results of the consumption model with the differenced hazard included. The Euler equation estimates suffer from omitted variable bias, since the differenced hazard also influences the differenced consumption, and the differenced hazard is negatively correlated with the lagged hazard.

4.5 Endogeneity concerns

The validity of the instrumenting strategy is violated if the death of a sibling has direct effect on the consumption expenditures. In the reduced form model the death of a sibling between the two waves and the death of all the siblings before wave one influence the consumption expenditures. If a sibling dies between the two waves then the consumption expenditures increase, and if none of the siblings are alive at wave one then the second wave expenditures are smaller relative to the first wave expenditures. I assume that this influencing mechanism works through the effect on the subjective mortality hazard. However, the death of a sibling can have direct effect on the expenditures if the deceased sibling was a member of the respondent's household at the time of the first observation or if the respondent received bequest from the deceased sibling.

Consumption is measured as household level expenditure on food divided by the household size. This measure might be directly affected by the death of the sibling living in the household if the expenditure is a nonlinear function of the household size. Because of this concern I reestimate the consumption models with excluding from the estimation sample the respondents whose deceased sibling was a household member in the first wave. This information is not directly included in the data, but two indicators can be used for this purpose. First, I exclude those individuals for whom the household size changed between the two waves (18% of the sample). Second, I exclude those who report that a sibling is a household member either in the first or the second wave (1% of the sample). The problem with the second restriction is that the relation of the household members to the respondent is unambiguous only for the so-called household respondent, and not for the spouse.

I also reestimate the models with excluding those individuals who report receiving gift or inheritance of 5 thousand Euro or more since the first wave, and for whom it can be identified that it was received from a sibling (less than 0.5% of the sample). With this restriction it can be analyzed if inheritance from the deceased sibling drives the estimation results.

I do not include the additional control variables in this estimations, and use only the sample of the individuals with positive wealth holdings. None of these restrictions influence the estimated sign and significance of the indicators of changing subjective hazard. The coefficients of the first differenced hazard and increasing hazard indicators remain significant at 5% significance level, indicating 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. The coefficient of the first wave hazard is also robust to these restrictions.

If the consumption preferences change after the death of a sibling then that can also violate the exogeneity of the instrument. In this paper the consumption measure is 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 with the death of a sibling or with the hazard shock. The first scenario implies that the instrument has direct effect on the consumption expenditures. However, the second scenario implies that the preferences are state dependent, and the utility function specified in section 2 is unrealistic. Based on the risk preference questions included in the Health and Retirement Study questionnaire, Barsky et al. (1997) document that the preference parameters of individuals aged 50+ are indeed heterogenous. In addition, Elder (2007) finds some evidence that subjective longevity increases the risk tolerance of the HRS respondents. Finkelstein et al. (2008) provide evidence that the marginal utility of consumption increases with health.

For the sake of analyzing 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, and I also analyze the adjustment of expenditure on food consumed away from home. The average share of expenditures on food consumed at home within the total food expenditures is 88% in the sample of people aged $50-80$ (the median is 91%). Table 8 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 do not include any additional control variables, and the IV estimation is applied. The estimated coefficients of the differenced hazard and increasing hazard indicators are similar in magnitude to the respective coefficients if the overall expenditure on food is used as consumption measure (Tables 5 and 6). The expenditure on food consumed at home is estimated to be adjusted upwards after the hazard shock slightly more than the total expenditure. This finding indicates that the adjustment takes place through this category of expenditures, and not through the expenditures on food consumed away from home

Differenced hazard as regressor

	Whole sample	Positive W
dhazard	5.813	9.067**
	[1.48]	[2.18]
l.hazard	0.755	1.539
	[0.57]	[1.03]

Increasing hazard indicator as regressor

	Whole sample	Positive W
hazard incr.	0.455	0.708**
	[1.51]	[2.34]
l.hazard	-2.550	-3.463*
	[1.33]	[1.70]

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

Table 8: IV estimation results, differenced logarithmic expenditure on food consumed at home as dependent variable

In both waves for around 60% of the respondents the amount spent on food away from home is zero. It can be analyzed how the propensity to consume food away from home is affected by a shock in the subjective hazard. The following bivariate probit model is estimated, written up on latent variables, denoted with stars:

$$\begin{aligned} pos\_wave2_i^* &= \theta_{10} + \theta_{11} H_i + w_{1i} \\ H_i^* &= \theta_{20} + \theta_{21} sibl\_die_i + w_{2i}, \end{aligned} \tag{26}$$

where pos_wave2_i is the binary indicator of positive expenditures on food consumed away from home in wave 2, and H_i is the binary indicator of an at least 1.5 percentage points decrease in the subjective survival probability. Estimating this bivariate probit model can handle the potential endogeneity of the hazard indicator in the model of food expenditures. However, if the death of a sibling has direct effect on the probability of consumption away from home then this simple model can not distinguish the direct and indirect effects. The model is estimated separately for those who report positive and zero expenditures in the first wave. The estimated marginal effects of increasing hazard are reported in Table 9.

These estimates indicate that consuming food away from home becomes less likely after a shock in the subjective hazard, which is considered as an evidence for changing preferences. This negative effect is significant for those respondents who report positive expenditures on food consumed away from home in the first survey wave. These results suggest that after the hazard shock, food consumed away from home might be substituted with consumption at home.

Positive expenditure in wave 1	
hazard incr.	-0.410***
	[3.79]
Zero expenditure in wave 1	
hazard incr.	-0.219
	[0.89]

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

Table 9: Average marginal effect of increasing subjective hazard on the probability of reporting positive expenditures on food consumed away from home in wave 2

To conclude, 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 results indicate that the preferences are state dependent, but based on these finding it cannot be decided whether the death of a sibling has a direct effect on the preferences or it has only indirect effect through the subjective hazard. Nevertheless, these results do not contradict the finding of section 4.3 that the total consumption expenditures are adjusted upwards as a consequence of the increasing subjective hazard.

4.6 Selectivity

If the sample is nonrandom then that can potentially cause bias in the estimated coefficients. Only those individuals are included in the estimations for whom both wave 1 and 2 observations are available. In addition, the indicator of subjective survival probability can not be missing. 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. Taking into account the item non-response to the subjective survival probability question, only 58% of the age-eligible wave 1 respondents can be included in the estimation sample.

Attrition is more likely for individuals with higher subjective mortality hazard in the first wave of the sample. The earlier death of siblings has no significant effect on the probability of attrition, but the number of siblings alive has significantly negative effect on that. This indicates that the death of a sibling might also be related to the inclusion in the sample. In addition, the willingness to respond in the first wave is a strong predictor of attrition.

The nonresponse rate to subjective survival probability in the sample is relatively high, around 8%. The item nonresponse rate varies across the countries, it is the highest in France (19%) and Spain (16%), lowest in Germany (4%), based on both waves of the survey, excluding the respondents aged above 80. Low propensity to report subjective survival probability can indicate that measurement errors are high in the observed survival probability and hazard indicators, provided that the reasons for the higher nonresponse rate are some difficulties in answering the question about survival probability. The probit model of item nonresponse indicates that the probability of not responding the survival probability question is higher for those who are older and who report worse health status.[13]

[13] A probit model of item nonresponse is estimated, where the indicator of noresponse is set to one if life expectancy is not reported either in the first or second wave, thus for whom the differenced survival probability is missing. The control variables besides the country dummies are the age, gender, marital status, education level, income, and self reported health status of the respondent. I also control for the interviewer's observation of declining willingness to answer during the interview. This is reasonable since the expectation questions are in the final block of the SHARE questionnaire, and by that time the respondents can become less willing to respond.

If the selection into the sample is related to the instruments used in the consumption model, 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. The effect of increasing mortality hazard indicator can be 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 two-year hazard (which is 0.02). This result suggests that the overall effect of a hazard shock is likely to be underestimated due to the attrition and to the higher item nonresponse rate among respondents with higher first wave mortality hazard.

5 Robustness and specification checks

5.1 Estimation sample

In the following robustness and specification checks only the hazard measures are included in the consumption models, the sample is restricted to individuals with positive wealth holdings, and only the IV estimates are analyzed. 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. In this estimation sample the oldest 1% is still excluded, for whom the item nonresponse rate to the survival probability question is above 30%, which indicates that for the very old the consumption model cannot provide reliable estimates. Since the influential role of subjective mortality hazard on consumption expenditure decisions for the individuals aged above 80 might be moderate and the reported survival probabilities are less reliable, in the basic estimates I exclude them from the estimation sample.

In Table 10 I present the results of the IV estimations, the first rows under both blocks include the reference results from section 4.3. The magnitude and significance of the estimated coefficients are strongly affected by the age restriction of the sample, but the estimated positive effect of increasing hazard is robust. The first wave hazard is estimated to have stronger and negative effect on the consumption path of the oldest individuals, provided that the differenced hazard is included in the model. On the other hand, the effect of increasing hazard becomes insignificant and close to zero if the individuals aged $80-90$ are included in the sample. One explanation for the sensitivity of the coefficients is the different strength of the instruments in the two samples: the explanatory power of the instruments on the lagged hazard indicator becomes stronger, whereas that 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 coefficients of the indicators of changing hazard.

In the benchmark specifications the hazard indicators are missing if the reported survival probability is zero, which affects around 5% of the estimation sample. Reporting zero survival probability is more likely for individuals with some health problems, and for older, not employed, and single individuals. This implies that due to rounding error 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, based on which assumption the subjective hazard

First differenced and increasing hazard coefficients

	dhazard coefficient	hazard incr. coefficient
2SLS	7.909**	0.612**
	[2.08]	[2.10]
2SLS, 80+ included	1.646	0.072
	[0.39]	[0.21]
2SLS, 0% probability included	4.293*	0.722*
	[1.86]	[1.93]
2SLS, pos. financial wealth	8.598*	0.730*
	[1.81]	[1.66]

Lagged hazard coefficients

	dhazard as regressor	hazard incr. as regressor
2SLS	0.382	-4.115*
	[0.26]	[2.13]
2SLS, 80+ included	-1.643*	-2.671*
	[1.66]	[1.70]
2SLS, 0% probability included	-0.664	-2.994*
	[0.71]	[1.93]
2SLS, pos. financial wealth	-0.431	-4.824*
	[0.26]	[1.93]

Absolute value of cluster robust t statistics in brackets

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

Table 10: Robustness checks with respect to the estimation sample: hazard indicator coefficients in the consumption models (IV estimation)

indicator can be calculated. The sign of the estimated adjustment after a hazard shock is unaffected by this modification, but the significance of the hazard shock indicators decreases. The lagged hazard coefficient remains insignificant or significant only at 10% significance level, depending on the specification. These findings suggest that the observed zero survival probabilities are rather due to measurement error than due to rounding to zero from a small probability.

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 non-financial wealth is illiquid and can not be used for financing consumption needs then the credit constraint can become binding also for those who have positive net worth but zero financial wealth holdings. 70% of the individuals in the sample have positive financial wealth holdings in both waves. The coefficients reported in Table 10 indicate that the effect of subjective hazard on consumption expenditures is stronger for individuals with positive financial wealth, and the signs of the effects are in line with the predictions of the life-cycle model. However, these estimated effects are only weakly significant. Again, the significance of the lagged hazard coefficient is not affected by this sample restriction.

The presented checks indicate that it is a robust finding that consumption expenditures are adjusted upwards if the subjective hazard increases. This adjustment is weaker for the oldest individuals. If the binary indicator of increasing hazard is included in the model then the negative coefficient of the first wave hazard is also a robust finding. However, if the differenced hazard is included in the model then the lagged hazard coefficient is sensitive to the selection of the estimation sample, the positive coefficient of the benchmark model is not a robust result.

5.2 Instrumental variables methods

This set of specification checks is with respect to the applied method of instrumental variables. The consumption models are exactly identified since only two instruments are used in the models and there are two endogenous variables. Therefore the two-stage least squares and limited information maximum likelihood estimations are identical. However, since there is some evidence that the instruments are weak,[14] 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 (which is a modified LIML estimator) with parameters 1 or 4.[15] An alternative can be the jackknife instrumental variables estimator (JIVE), which can mitigate the finite-sample bias of the 2SLS estimator. I consider two alternatives: 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 (JIVE1), and the method suggested by Blomquist and Dahlberg (1999) where the jackknife first stage fitted value is used as a regressor in the second stage OLS estimation (JIVE2).[16] These results are presented in Table 11, where the benchmark 2SLS estimates are also presented. Again, only the results for individuals with positive wealth holdings are analyzed.

The estimated sign and significance of the hazard indicators are robust to the alternative estimation methods. It is a robust finding that the estimated effect of increasing hazard is positive on consumption expenditures. This effect is significant at 10% or 5% significance level both if the first differenced hazard and if the increasing hazard dummy is used as regressor. The effect of the hazard shock is estimated to be stronger if the jackknife instrumental variables estimator suggested by Angrist et al. (1999) are used. The point estimates of the Blomquist and Dahlberg (1999) type estimation are close to the benchmark two-stage least squares estimates. If the additional control variable in the model is the binary indicator of increasing hazard then the results reinforce that the ex ante effect of subjective hazard on the consumption path is negative. This effect is significant at 5% significance level. However, the lagged hazard coefficient remains positive and insignificant if the differenced hazard is included in the model.

It can be concluded that the adjustment of consumption expenditures after a hazard shock can be reliably estimated by the preferred 2SLS estimation method. Increasing subjective mortality hazard is estimated to have positive effect on consumption expenditures. These results change only slightly if Fuller's estimator or the jackknife instrumental variable methods are applied.

The next specification check is with respect to the instruments used. I repeat the estimations with including as instrumental variables also the age or age of death of parents in the first wave, and the binary indicators of the death of a parent between the two waves. As discussed in section 4.2, using the age or the death of the parents as instruments raises endogeneity concerns. Nevertheless, this specification check can

[14] The Stock-Yogo critical values reported after the *ivreg2* command in Stata indicate that the problem of weak instruments is present in the estimated consumption models, especially if the differenced hazard is included in the model. The values of the Kleinbergen-Paap rk F-statistic lie between $4-7$, depending on the specification, with smaller values if additional regressors are included in the models.

[15] 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 $W'P_ZW(W'M_ZW)^{-1}$ with $W=[Y,X]$.

For Fuller's estimator $k = \lambda - \frac{a}{N-K}$, 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).

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

In his Monte Carlo simulations Poi (2006) reports cases where the two types of JIVE results give considerably different estimates. In addition, both Hahn et al. (2004) and Davidson and MacKinnon (2006) caution against using the jackknife IV estimators based on the bias, dispersion, and reliability of the estimates.

First differenced and increasing hazard coefficients

	dhazard coefficient	hazard incr. coefficient
2SLS	7.909**	0.612**
	[2.08]	[2.10]
Fuller(1)	7.338**	0.585**
	[2.14]	[2.12]
Fuller(4)	6.023**	0.517**
	[2.28]	[2.17]
JIVE1	10.934*	0.732**
	[1.82]	[2.11]
JIVE2	7.871**	0.612**
	[2.06]	[2.17]
LIML, additional instruments	9.792*	0.435
	[1.65]	[1.61]

Lagged hazard coefficients

	dhazard as regressor	hazard incr. as regressor
2SLS	0.382	-4.115*
	[0.26]	[2.13]
Fuller(1)	0.315	-3.972**
	[0.23]	[2.14]
Fuller(4)	0.159	-3.606**
	[0.13]	[2.17]
JIVE1	0.696	-4.778**
	[0.40]	[2.35]
JIVE2	0.379	-4.113**
	[0.26]	[2.43]
LIML, additional instruments	1.667	-1.959
	[1.02]	[1.45]

Absolute value of t statistics in brackets (cluster robust under 2SLS, LIML and Fuller estimates)
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 11: Specification checks with respect to the IV estimation method: hazard indicator coefficients in the consumption models

provide evidence how sensitive are the results to the applied instrumenting strategy. Since there is some evidence that the instruments are weak, the more reliable limited information maximum likelihood estimation (LIML) is applied instead of the two-stage least squares procedure (for details see Staiger and Stock (1997)). The results are also presented in Table 11.

Extending the list of instruments has some effect on the estimated coefficients of the first differenced hazard and increasing hazard binary indicators, but those remain positive, and the differenced hazard remains significant at 10% significance level. The coefficient of the first wave hazard is more sensitive to the instrumenting strategy, and it becomes insignificant also if the binary indicator of increasing hazard is included in the model. The indicators of the strength of the instruments show that including additional instruments aggravates the problem of weak instruments, which makes the point estimates of the coefficients less reliable. In addition, the exogeneity of the indicators of parents' age and parents' death in the consumption model is questionable. These results do not invalidate the previously estimated positive effect of increasing hazard on consumption expenditures, and also indicate that the estimated ex ante effect of mortality hazard is more sensitive to the choice of instruments.

5.3 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. If the credit constraint is binding for an individual who expects increasing income, then the expected consumption path can be positively sloped. This might hold especially for the younger respondents who are active in the labor market. The optimal consumption path is also modified if income is uncertain. If uncertainty is introduced to the life-cycle model then a modified Euler equation can be derived, following Carroll (2001):

$$E_t\left(\frac{C_{it+1}}{C_{it}}\right) = \left(E_t\left(I_{it+1}\right)\beta R\right)^{\frac{1}{\gamma}} V_i^{\frac{\gamma+1}{2}}, \tag{27}$$

where $V_i \geq 1$ is an individual-specific measure of income uncertainty. This expression implies that 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 realized.

As an indicator of time varying income the employment status of the respondent is used. For the sake of simplification, the respondent is defined to be retired if he does not report employment or self employment in any of the two waves of questionnaire (66% of the respondent in the estimation sample). If the consumption models are estimated on the subsample of retired individuals then the IV estimates of the increasing hazard indicators become stronger, and remain significant at 5% significance level. Excluding additional control variables, and estimating the model on the sample of those retired individuals who have positive wealth, the estimated coefficient of the differenced hazard becomes 9.16 (previously 7.91), and the coefficient of the dummy of increasing hazard becomes 0.74 (previously 0.61).

Thus the effect of increasing hazard on consumption expenditures is stronger for those who are not employed. On the other hand, no evidence is found that ex ante effect of mortality hazard on consumption path would also be stronger, and it remains positive if the differenced hazard is included in the model.

The influencing effect of subjective mortality hazard on the consumption expenditures can also be weaker if the consumption decision is not an individual decision, but for example a joint decision of the household members. The presented life-cycle model assumes that the consumption is a result of the individual optimizing behavior. The model also assumes that there are no bequest motives. Although in two related papers Hurd (1989) and Gan et al. (2004) find using HRS data that bequest motives are weak, such motives can still have some influence on consumption decisions. If the life-cycle model is extended with bequest motive then the model can be solved only numerically. However, a closed form solution can be derived in a simple two-period model, which indicates that the partial effect of mortality hazard on the consumption level becomes smaller with bequest motives.[17]

The most reliable 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

[17] The following simplifying assumption is 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.

Under this assumption it can be derived that 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.

estimates become imprecise with t statistics close to zero. The similar holds if the bequest motives and joint decisions are indicated by living in non single households. Restricting the sample to single households would necessitate the exclusion of 84% of the otherwise eligible observations.

Receiving social support from someone outside the household can also indicate that the consumption expenditures do not result from individual decisions, and it can also indicate bequest motives. Therefore, receiving social support can weaken the effect of subjective hazard on consumption expenditures. I define an individual to receive social support if he reports receiving personal care or practical household help from someone outside the household during the 12 months prior to the interview in any of the two waves.[18] 25% of the respondents included in the estimating sample have received such support in any of the two waves. The majority of the support is practical household help, and the help is typically provided by the children of the respondents (less than 10% of the help is received from a sibling). However, if the sample is restricted to those who do not receive social support then the positive effect of increasing hazard on consumption expenditures becomes stronger only if the binary indicator of increasing hazard is used. Both the differenced hazard and the binary indicator of increasing hazard remain significant at 5% significance level, with coefficients of 7.17 and 0.95, respectively.

It can be concluded that no empirical evidence could be found that bequest motives or joint decisions would significantly affect the effect of subjective hazard on consumption expenditures.

6 Concluding remarks

The life-cycle model with uncertain lifetime predicts that the effect of the subjective mortality hazard on the expected consumption dynamics is negative, whereas an upward shock in the mortality hazard leads to higher consumption expenditures. These effects hold only for those individuals for whom the assumed credit constraint is not binding. The main novelty of this paper is to identify the influencing role of changing hazard on consumption expenditures. The effects of the subjective hazard measures are identified by using the death of a sibling as instrument. Using the first two waves of the Survey of Health, Ageing and Retirement in Europe, the indicators of the death of a sibling between the two survey waves and before the first wave are used as instruments for the differenced hazard and first wave hazard indicators.

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 upwards after a 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. Consumption is measured with expenditure on food, and the results indicate that the upwards adjustment after the hazard shock takes place through the adjustment of expenditures on food consumed at home. 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.

Some evidence is also found for the negative effect of first period mortality hazard on the consumption dynamics, which is predicted 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.

[18] Due to the survey design, receiving financial transfers cannot be reliably included in this analysis. The survey asks only about receiving financial gifts amounting 250 EUR or more. Only 4% of the respondents in the second wave report receiving such gift.

Estimating the Euler equation with neglecting the effect of changing hazard can lead to biased estimates since the initial hazard, which is included in the Euler equation is correlated with the hazard shock, which is excluded from the Euler equation.

The limitations of the finding about the adjustment of consumption expenditures have to be kept in mind: it is based on only two observation years, and a selective European sample is used, thus the evidence for adjustment might not be valid in less developed countries. In addition, these results 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. Using the U.K. and U.S. counterparts of the SHARE data (the Health and Retirement Study, HRS and the English Longitudinal Study of Ageing, ELSA data sets) could reveal some potential cross-country differences in the influencing effect of the hazard shocks. As part of the future research, I plan to analyze the effect of subjective mortality hazard on consumption preferences, which analysis could also reveal if changing expected longevity has significant effect on the consumption structure.

Appendix: consumption model estimation results

A Differenced hazard as regressor

	Whole sample		Positive wealth	
	IV	OLS	IV	OLS
dhazard	5.429	-0.147	8.932*	-0.173
	[1.20]	[1.17]	[1.82]	[1.35]
l.hazard	0.003	-0.468*	1.553	-0.495*
	[0.00]	[1.83]	[0.28]	[1.86]
mother dies	0.004	0.014	-0.002	0.013
	[0.15]	[0.61]	[0.07]	[0.55]
father dies	-0.027	-0.020	-0.040	-0.028
	[0.83]	[0.65]	[1.11]	[0.88]
dln_inc	0.015***	0.014***	0.017***	0.015***
	[3.67]	[4.42]	[3.61]	[4.54]
age	-0.001	-0.001	-0.004	-0.001
	[0.09]	[1.06]	[0.31]	[0.93]
female	0.012	-0.007	0.023	-0.010
	[0.56]	[0.88]	[0.95]	[1.17]
has child	0.024	0.024	0.017	0.018
	[0.92]	[1.04]	[0.66]	[0.78]
new_cancer	-0.369*	-0.287	-0.412*	-0.286
	[1.77]	[1.57]	[1.77]	[1.48]
new_heart attack	-0.037	0.083	-0.155	0.047
	[0.28]	[1.18]	[1.06]	[0.62]
new_stroke	0.092	0.020	0.094	0.054
	[0.85]	[0.27]	[0.75]	[0.74]
new_fracture	0.050	0.076	-0.020	0.077
	[0.24]	[0.29]	[0.08]	[0.20]
new_hypertension	-0.023	0.003	-0.041	0.002
	[0.81]	[0.21]	[1.18]	[0.12]
new_high cholesterol	0.021	0.017	0.017	0.011
	[1.02]	[1.00]	[0.71]	[0.63]
new_diabetes	-0.018	-0.064	0.013	-0.058
	[0.32]	[1.64]	[0.21]	[1.60]
new ADL limitation	-0.090	-0.045	-0.105	-0.020
	[0.94]	[1.18]	[0.89]	[0.61]
ddepression	-0.038	-0.002	-0.047	0.011
	[1.36]	[0.13]	[1.43]	[0.80]
exit_emp	-0.089***	-0.082***	-0.075**	-0.065**
	[2.75]	[2.70]	[2.23]	[2.27]
become_single	0.173***	0.196***	0.194***	0.234***
	[3.24]	[4.02]	[3.59]	[6.05]
DE	-0.074**	-0.072**	-0.071*	-0.068**
	[2.24]	[2.43]	[1.90]	[2.24]
SE	-0.059	-0.034	-0.077*	-0.036
	[1.51]	[1.15]	[1.65]	[1.17]
NL	-0.072*	-0.056*	-0.060	-0.045
	[1.65]	[1.83]	[1.28]	[1.51]
ES	-0.029	0.007	-0.045	0.002
	[0.68]	[0.21]	[0.94]	[0.07]
IT	-0.065	-0.069**	-0.059	-0.071**
	[1.59]	[2.46]	[1.27]	[2.43]
FR	-0.048	-0.031	-0.052	-0.027
	[1.39]	[1.08]	[1.35]	[0.92]
DK	-0.090	-0.079*	-0.041	-0.042
	[1.53]	[1.84]	[0.63]	[1.03]
GR	-0.001	-0.003	0.003	-0.008
	[0.02]	[0.13]	[0.10]	[0.31]
CH	-0.131***	-0.123***	-0.118**	-0.116***
	[2.75]	[3.40]	[2.25]	[3.10]
BE	-0.082**	-0.061**	-0.097**	-0.061**
	[2.21]	[2.24]	[2.37]	[2.19]
Constant	0.075	0.111*	0.193	0.114*
	[0.15]	[1.66]	[0.34]	[1.70]
Observations	13,280	13,280	12,583	12,583

Absolute value of cluster robust t statistics in brackets

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

B Increasing hazard as regressor

	Whole sample		Positive wealth	
	IV	OLS	IV	OLS
hazard incr.	0.401	-0.007	0.651	-0.007
	[1.03]	[0.57]	[1.60]	[0.53]
l.hazard	-5.089	-0.306	-5.818	-0.318
	[1.11]	[1.33]	[1.26]	[1.32]
mother dies	-0.014	0.017	-0.031	0.015
	[0.43]	[0.73]	[0.87]	[0.63]
father dies	-0.051	-0.020	-0.074*	-0.028
	[1.31]	[0.67]	[1.75]	[0.89]
dln_inc	0.013***	0.015***	0.014***	0.016***
	[3.38]	[4.65]	[3.25]	[4.74]
age	0.005	-0.002*	0.004	-0.001
	[0.45]	[1.70]	[0.35]	[1.49]
female	-0.011	-0.011	-0.012	-0.012
	[0.88]	[1.26]	[0.81]	[1.44]
has child	0.030	0.037	0.019	0.025
	[1.11]	[1.50]	[0.73]	[1.08]
new_cancer	-0.267	-0.206	-0.309	-0.200
	[1.44]	[1.27]	[1.53]	[1.18]
new_heart attack	0.151	0.119*	0.047	0.079
	[1.11]	[1.76]	[0.43]	[1.08]
new_stroke	0.127	0.011	0.168	0.046
	[1.09]	[0.15]	[1.38]	[0.64]
new_fracture	0.023	0.080	-0.069	0.078
	[0.10]	[0.33]	[0.20]	[0.21]
new_hypertension	-0.006	0.008	-0.014	0.006
	[0.29]	[0.52]	[0.63]	[0.41]
new_high cholesterol	0.028	0.020	0.022	0.014
	[1.34]	[1.17]	[0.98]	[0.80]
new_diabetes	-0.010	-0.065*	0.012	-0.055
	[0.17]	[1.71]	[0.19]	[1.57]
new ADL limitation	-0.052	-0.065*	-0.048	-0.048
	[0.70]	[1.71]	[0.58]	[1.42]
ddepression	-0.031	-0.006	-0.031	0.006
	[1.44]	[0.42]	[1.36]	[0.46]
exit_emp	-0.113***	-0.082***	-0.113***	-0.067**
	[2.99]	[2.75]	[2.95]	[2.37]
become_single	0.207***	0.225***	0.217***	0.259***
	[3.84]	[4.91]	[3.78]	[7.09]
DE	-0.061*	-0.074**	-0.038	-0.063**
	[1.68]	[2.40]	[0.96]	[2.02]
SE	-0.041	-0.029	-0.040	-0.030
	[1.10]	[0.97]	[0.94]	[0.96]
NL	-0.083*	-0.060*	-0.061	-0.048
	[1.69]	[1.91]	[1.18]	[1.53]
ES	-0.042	0.012	-0.057	0.010
	[0.80]	[0.38]	[1.08]	[0.29]
IT	-0.070*	-0.061**	-0.058	-0.061**
	[1.67]	[2.12]	[1.26]	[2.05]
FR	-0.031	-0.029	-0.021	-0.024
	[0.92]	[0.99]	[0.57]	[0.81]
DK	-0.092	-0.073*	-0.044	-0.036
	[1.46]	[1.69]	[0.63]	[0.88]
GR	0.025	0.002	0.049	-0.002
	[0.51]	[0.07]	[0.87]	[0.07]
CH	-0.148***	-0.119***	-0.133**	-0.112***
	[2.87]	[3.27]	[2.44]	[2.97]
BE	-0.045	-0.060**	-0.035	-0.059**
	[1.42]	[2.13]	[1.01]	[2.03]
Constant	-0.230	0.138**	-0.206	0.138**
	[0.42]	[2.03]	[0.36]	[2.03]
Observations	13,652	13,652	12,917	12,917

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

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