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# ABSTRACT

## Well-Being over the Life Span: Semiparametric Evidence from British and German Longitudinal Data*

This paper applies semiparametric regression models using penalized splines to investigate the profile of well-being over the life span. Splines have the advantage that they do not require a priori assumptions about the form of the curve. Using data from the British Household Panel Survey (BHPS) and the German Socio-Economic Panel Study (SOEP), the analysis shows a common, quite similar, age-specific pattern of life satisfaction for both Britain and Germany that can be characterized by three age stages. In the first stage, life satisfaction declines until approximately the fifth life decade. In the second age stage, well-being clearly increases and has a second turning point (maximum) after which well-being decreases in the third age stage. Several reasons for the three-phase pattern are discussed. We point to the fact that neither polynomial functions of the third nor the fourth degree describe the relationship adequately: polynomials locate the minimum and the maximum imprecisely. In addition, our analysis discusses the indistinguishability of age, period, and cohort effects: we propose estimating age-period models that control for cohort effects including substantive variables, such as the life expectancy of the birth cohort, and further observed socioeconomic characteristics in the regression.

JEL Classification: C14, C23, D10, I31

Keywords: subjective well-being, life satisfaction, semiparametric regression, penalized splines, age-period model, age-cohort model

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## 1 Introduction

One of the core issues of economic analysis is the question of how a rational person should choose between present consumption and saving for future consumption to maximize his/her lifetime utility. Knowledge of the resulting path of utility over the life cycle is useful for economic and political decision makers aiming at increasing people's happiness. For example, if young people in the family-formation stage report a significant decline in their (financial) satisfaction, then state incentives could promote saving for retirement that would not be done otherwise. Such support could be stopped after well-being has reached a minimum and begins to rise again. In this way, the state incentives may induce a balancing effect on the utility profile and promote the continuity of saving. Another example is the optimal timing of pay increases: the utility profile provides valuable information about the age at which pay increases are most helpful to compensate for decreases in job satisfaction.

However, the life cycle utility derived from theoretical intertemporal models depends largely on the assumptions of these models. Even worse, different but equally plausible assumptions may result in opposing predictions so that increasing, decreasing or constant utility profiles can be hypothesized (cf. Shmanske 1997, Blanchflower and Oswald 2008). Therefore, it is unclear which theoretical assumptions describe the true well-being appropriately.

Because theoretical models do not lead to unambiguous conclusions, the profile of utility over the life cycle must be identified by empirical investigations. However, previous empirical findings do not provide clear results. Moreover, we suspect that the U-shaped relationship between well-being and age frequently found in empirical analyses is predetermined by the quadratic functional forms used in the econometric models often applied in the literature.

This paper attempts to reveal the path of well-being over a the life span. We apply semiparametric regression models using penalized splines that do not rely on an a priori specification of the functional form of the estimation equation. The paper is organized as follows: Section 2 briefly summarizes the existing research. Some theoretical considerations on the determinants of life cycle utility and the indistinguishability of age, period, and cohort effects are given in

Section 3. The estimation strategy and data are introduced in Section 4 and Section 5, respectively. Section 6 presents the empirical evidence, and Section 7 provides concluding comments.

## 2 Review of the literature

Empirical studies of the relationship between well-being and age can be divided into two major groups: those that support the U-shape and those that are inconsistent with it. The former are mostly economic studies, whereas the latter often come from the field of psychology. This section introduces some selected works from these respective positions.

In the psychology literature, three components of subjective well-being are identified: pleasant (positive) and unpleasant (negative) affects represent emotional responses, whereas life satisfaction is regarded as the cognitive aspect of well-being (e.g., Lucas et al. 1996, Diener et al. 1999). Empirical investigations of these components of well-being present the following results: the analysis of Mroczek and Kolarz (1998) indicates a curvilinear effect of age on the positive affect. Correspondingly, Charles et al. (2001) find that the negative affect decreases with age, which is attributed to the fact that people more successfully construct environments that promote well-being as they grow older. Hence, one can conclude that the overall improvement of the affective state contributes to an increase in subjective well-being over the life cycle. With respect to life satisfaction, Mroczek and Spiro (2005) find an inverted U-shape with a peak at age 65 in a sample of approximately 2000 male respondents aged 40 to 85 years from the Veterans Affairs Normative Aging Study.

Easterlin (2006) analyzes pseudo panel data (i.e., repeated cross sections) from the General Social Survey (GSS) of the US by applying a refined variant of demographer's birth cohort analysis. An ordered logit regression of happiness on age (and its square) indicates an inverted U-shaped relationship between well-being and age while controlling for year of birth, sex, race, and education. The path of certain domain satisfactions over time is regarded as the underlying reason for this pattern: the inclining part of the curve up to midlife is supposed to result from the growth in satisfaction with family life and work. Later in life, a deterioration of health and decreasing satisfaction with family life leads to an overall reduction in life satisfaction.

Using the West Germany subsample of the Socio-Economic Panel Study (SOEP) and applying structural equation modeling, Schilling (2006) finds a high monotonic stability of life satisfaction within one year. Adaptation is considered to be responsible for the rather unchanged satisfaction levels across the life span. However, a limitation of this study is that it does not control for socioeconomic characteristics such as sex, education, or health. Kassenboehmer and Haisken-DeNew (2008), who also use data from the SOEP, do not find an age effect when controlling for socioeconomic characteristics, individual specific fixed effects, years of participation in the panel, and interviewer characteristics.

Early empirical evidence in favor of the U-shaped well-being profile over the life span is provided in Latten (1989). Using approximately 3000 Dutch respondents aged 18 years and older from four waves of the Quality of Life Survey carried out between 1974 and 1983, the estimation of third-order polynomial regressions indicates that life satisfaction declines from the age of 30 onwards and reaches a minimum in midlife between the ages of 50 and 60. Higher occurrence of tensions at home and illnesses are discussed as reasons for the decline in well-being. From the age of 55 onwards, an increase in satisfaction is detected. A persuasive explanation of the higher levels of well-being in old-age is, however, not given.

The U-shaped well-being profile is also found in some more recent studies. For example, Blanchflower and Oswald (2004) find the minimum of well-being to be around the age of 40 using data from both the GSS and the Eurobarometer Survey. The authors hypothesize that a process of adaptation to circumstances is at work: “perhaps, by the middle of their lives, people relinquish some of their aspirations and thereby come to enjoy life more” (p. 1375). On the basis of large international data sets, Blanchflower and Oswald (2008) describe a general life cycle pattern that has a minimum between 40 and 50 years of age for most countries. The authors use multivariate regression analysis controlling for socioeconomic characteristics, fixed year effects, and for cohort effects. In addition to a quadratic specification of the model, the authors also use dummy variables comprising age groups of five years. The results suggest a second turning point later in life, and from that point onwards the well-being curve turns downwards.

Clark (2007) approaches the research question in a similar fashion: using respondents aged from 16 to 64 years of the British Household Panel Survey (BHPS), the analysis investigates to what extent the U-shaped well-being profile is caused by cohort effects. The central research question is to disentangle age and cohort effects using fixed effects regressions that control for the cohort effect as part of the individual specific fixed effect. Including age dummies representing five-year age-blocks allows the estimation of the relationship between well-being and age in a nonparametric way. In addition, the regressions control for fixed year effects including wave dummies. The results indicate that, even after controlling for cohort and period effects, the U-shape can still be found in the data. This approach suggested by Clark has been adopted by two recent studies using German data (cf. van Landeghem 2008, Gwozdz and Sousa-Poza 2009). We comment on the identifiability of age, period, and cohort effects in the next section.

Additional references to economic studies supporting the U-shaped well-being profile can be found in Blanchflower and Oswald (2004), Clark and Oswald (2006), and Clark (2007). Diener and Suh (1997) provide a comprehensive review of the psychology literature.

## 3 Indistinguishability of age, period, and cohort effects

The studies by Clark (2007) and Blanchflower and Oswald (2008) cited in the previous section are examples of research projects aimed at simultaneously identifying age, period, and cohort effects on well-being. However, they do not address explicitly the identification problem. The identification problem arises because of the fact that $age = period - cohort$ makes the effects indistinguishable (cf. Clayton and Schifflers 1987a, b). The researchers overcome the problem of perfect colinearity of age and period while controlling for cohort using a reparameterization of the age-period-cohort model: respondents belonging to different age groups are arranged in five-year age-blocks. The dummy variables generated in this way are then substituted for the linear (and quadratic) age terms. (In a similar manner, Blanchflower and Oswald (2008) create, in addition, cohort categories comprising respondents born in an age range of 10 years.)

However, estimating age, period, and cohort effects in a multiple classification framework is only possible assuming that several age groups, time periods, or cohorts have identical effects on well-being (cf. Mason et al. 1973). That is, the age effects for respondents of different age groups lumped in one category are assumed to be of equal size. Markus (1983) offers objections to assumptions of this kind: first, the identification restrictions usually lack plausible arguments for imposing them, and second, in the case where plausible identification restrictions can be made, the estimation results are often highly sensitive to variations in the data. Therefore, a mathematical-statistical reformulation of the model is regarded to be less important for a solution to the identification problem than explicitly controlling for the influences underlying the processes that are represented by age, period, and cohort. In the following discussion, we consider these underlying processes.

A stylized equation that describes subjective well-being over the life cycle can be written as:

$$u_{it} = \beta_a age_{it} + \beta_p period_t + \beta_c cohort_i. \tag{1}$$

The question of functional form will be discussed in detail in the subsequent sections and is of no further interest at this point. Equation 1 says that the utility $u$ of an individual $i$ at time $t$ depends on age, time period, and birth cohort. Following Heckman and Hobb (1985), we argue that the justification for including age, period, and cohort as determinants in an economic model is that these variables represent proxy variables for other underlying factors or unobserved characteristics of the individual.

There are arguments supporting the view that age, period, and cohort determine utility over the life cycle. First, age has an impact on subjective well-being through various modes of action. In an economic context, in addition to utility from current consumption experiences, memory and anticipation are also supposed to have an impact on well-being (cf. Elster and Loewenstein 1992). Age can be interpreted as a proxy variable that captures these effects: for example, the number of pleasurable and memorable events experienced is supposed to vary as people grow older. Moreover, age may also be a proxy variable for unobserved effects such as needs that occur in different life stages or latent health characteristics.

Second, the period or year effect, $\beta_p$, measures the aggregate impact of the time period on well-being that equally affects all age groups simultaneously. The common experiences that are regarded as defining our era (e.g., the 9/11 attacks, or economic development such as the bursting of the dot-com bubble) are very likely to also have an impact on life satisfaction. The time period can be interpreted as a proxy for information about the aggregate development of such issues at the macro level. In this context, Di Tella et al. (2001) provide evidence that self-reported well-being depends on the unemployment rate and inflation. Wunder et al. (2008) show that the introduction of the euro cash in Germany was followed by a sharp decline in financial satisfaction.

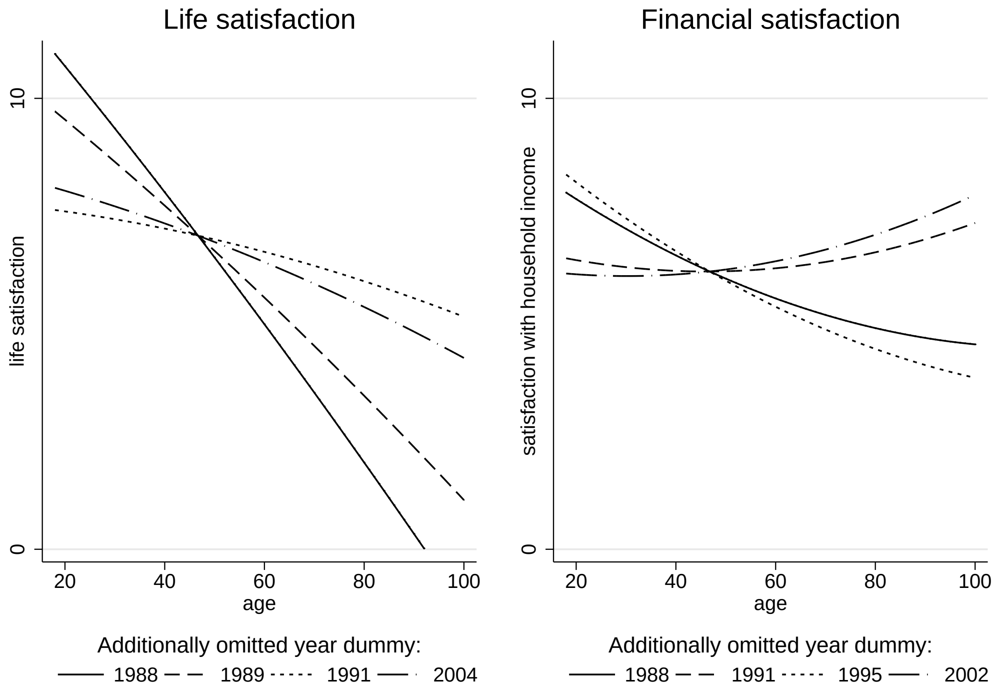
Third, the cohort effect, $\beta_c$, captures the influences that affect subjective well-being in a specific birth cohort equally throughout life. For example, some birth cohorts have to suffer from more economic disadvantages than others: Welch (1979) points to the effect of the arrival of a large birth cohort, the World War II baby boomers, on the labor market, which has negative consequences for the earnings of this cohort. In addition, both physiological as well as psychological effects may arise from economic and political changes. In this context, Kasen et al. (2003) provide evidence that the increased labor force participation of married women with children, which was a result of social change in the 1960s and 1970s, has led to increases in depression in recent birth cohorts.

In the following example, we illustrate the indistinguishability of age, period, and cohort effects in equation 1. We apply an individual fixed-effects model that is widely used by econometricians because it allows an unbiased estimation when the explanatory variables are correlated with the unobserved heterogeneity. In the context of the research question under consideration, the fixed-effects model controls implicitly for the cohort effect as part of the time-invariant, individual specific effect. However, in this framework, it is not possible to identify age and period effects without imposing further restrictions. The reason for this is that including a full set of $T-1$ year dummies (or, alternatively, a linear time trend) in addition to the individual's age, one is not able to estimate the effect of age because it is indistinguishable from the period effects. To make the parameters identifiable, one further year dummy is dropped from the list of the right-hand side variables so that only $T-2$ year dummies are included. In this case, the identification restriction assumes that the additional year omitted has no effect on the response variable.

The ambiguity of the results is illustrated in Figure 1. The graphs show second-order polynomial well-being equations. The results plotted in Figure 1 are obtained from identical regression equations with 1986 as the reference year. The regressions differ only with respect to the additionally omitted year dummy. It is obvious that this approach (i.e., a fixed-effects age-period-cohort model) to investigating the relationship between well-being and age does not lead to unambiguous results. The indistinguishability is also evident from the estimation results in Tables 4 and 5 in the Appendix: the estimator of the linear age effect clearly depends on the additionally omitted year dummy.

A solution to the colinearity problem is to decide between an age-period model (assuming no unobserved cohort effects) and an age-cohort model (assuming no unobserved period effects) when investigating the relationship between well-being and age. We propose an age-period model that captures the cohort effect through several causal variables. In an economic context, the cohort effect may represent, as mentioned above, the consequences of the entrance of a large birth cohort on the labor market. In addition, the cohort effect may also reflect the exposure to certain environmental circumstances, e.g., poor nutrition in the period after World War II. However, these effects can be directly controlled for in the regression equation. For example, we are able to model the increased risk of being unemployed faced by members of large birth cohorts directly, including the current labor force status in the regression. Long-term consequences of poor nutrition are captured by the health-related variables. As a consequence, we believe that an age-period model controlling for cohort-specific characteristics is most suitable for the question investigated in our study.

**Figure 1**
**Indistinguishability of age and period effects using a fixed-effects estimator**




*Note*: The fixed effects regression equations are identical except for the additionally omitted year dummy. The estimation results can be found in the Appendix, in Tables 4 and 5.
*Source*: SOEP 1986-2007 (without 1990, 1993)

## 4 Semiparametric regression using penalized splines (P-splines)

The difficulty in modeling the nonlinear effect of age on well-being with a parametric ad hoc specification arises, inter alia, from the fact that theoretical models lack unambiguous predictions regarding the utility profile over the life span. Therefore, the present paper applies a semiparametric regression approach that allows flexible estimation of nonlinear effects. In particular, the approach does not require a priori assumptions about the functional form. Instead, it is assumed that the profile of well-being over the life cycle obeys a semiparametric model:

$$y_{it} = \mathbf{c}'_{it}\boldsymbol{\alpha} + \eta(a_{it}) + \varepsilon_{it}, \quad i = 1, ..., n, \quad t \in T_i \subset \{1, ..., T\}. \tag{2}$$

Equation 2 says that the response $y$ of the $i$-th individual at time $t$ depends linearly on the covariates in the vector $\mathbf{c}$. This parametric component controls for the effects of socioeconomic characteristics other than age, such as education, income, labor force status, etc. The nonparametric component $\eta(a_{it})$ models the relationship between the response variable and age $a$ (given the covariates in $\mathbf{c}$), which is allowed to be nonlinear, but the particular form is not specified. $\varepsilon$ is the error that can be explained neither by the parametric nor by the nonparametric component.

Following Ruppert et al. (2003) and Wu and Zhang (2006), we use penalized splines (P-splines) to estimate the smoothing function $\eta(a_{it})$. Compared with other existing smoothing techniques, P-splines have the advantage that their performance does not depend so much on the location and number of knots (compared with regression spline methods) and that they are less computationally intensive (compared with smoothing spline methods). Moreover, as P-splines can be formulated within a linear mixed-model framework, standard software packages for mixed-model analysis can be used for smoothing (cf. Ngo and Wand 2004). We use the command -xtmixed- available in Stata 10 MP.

A P-spline uses a $k$-th degree truncated power basis $\mathbf{\Phi}_p(a)$ with $K$ knots $\tau_1, \tau_2, ..., \tau_K$:

$$\mathbf{\Phi}_p(a) = (1, a, ..., a^k, (a-\tau_1)_+^k, ..., (a-\tau_K)_+^k)', \tag{3}$$

where $(a-\tau_r)_+ = \max(0, (a-\tau_r))$ and $r = 1, ..., K$. The number of knots can be selected roughly and their location may be obtained, for example, using the equally spaced method or the equally spaced sample quantiles method (for details, cf. Wu and Zhang 2006). The first $(k+1)$ basis functions of the truncated power basis represent a polynomial function of $k$-th degree, and the remaining arguments denote truncated power functions of degree $k$. The number of basis functions involved is $p = K + k + 1$.

The estimated P-spline function can be written as follows:

$$\hat{\eta}(a) = \mathbf{\Phi}_p'(a)\hat{\beta}. \tag{4}$$

It is clear from equation 4 that the smoothing function is nonparametric in the sense that the function contains a large number of parameters that cannot be interpreted individually. Instead, the shape of the function is the main point of interest. The estimators $\hat{\boldsymbol{\beta}}$ and $\hat{\boldsymbol{\alpha}}$ are chosen so that they minimize the penalized least squares (PLS) criterion (cf. Wu and Zhang 2006):

$$\| \mathbf{y} - \mathbf{C}\boldsymbol{\alpha} - \mathbf{X}\boldsymbol{\beta} \|^2 + \lambda \boldsymbol{\beta}'\mathbf{G}\boldsymbol{\beta}, \tag{5}$$

where $\mathbf{y}, \mathbf{C}, \mathbf{X}$ are defined in correspondence to equation 2 as $\mathbf{y} = (y_{11}, \ldots, y_{nT_n})'$, $\mathbf{C} = (\mathbf{c}'_{11}, \ldots, \mathbf{c}'_{nT_n})'$, and $\mathbf{X} = (\mathbf{x}'_{11}, \ldots, \mathbf{x}'_{nT_n})'$ with $\mathbf{x}_{it} = \boldsymbol{\Phi}_p(a_{it})$. The so-called roughness matrix:

$$\mathbf{G} = \begin{pmatrix} \mathbf{0}_{(k+1)\times(k+1)} & \mathbf{0}_{(k+1)\times K} \\ \mathbf{0}_{K\times(k+1)} & \mathbf{I}_K, \end{pmatrix}_{p\times p} \tag{6}$$

allows us to penalize the $k$-times derivative jump of the regression spline. $\lambda$ is the smoothing parameter.

We apply a linear mixed-model framework to minimize the PLS criterion in equation 5, i.e., the estimators $\hat{\boldsymbol{\alpha}}$ and $\hat{\eta}$ are obtained from the best linear unbiased predictors (BLUPs) of a mixed model. For that purpose, the vector $\boldsymbol{\beta}$ has to be split into two subvectors, $\boldsymbol{\delta}$ and $\mathbf{u}$, containing the first $(k+1)$ and last $K$ elements of $\boldsymbol{\beta}$. The corresponding matrices are denoted $\tilde{\mathbf{X}}$ and $\tilde{\mathbf{Z}}$. Then the PLS criterion in equation 5 can be reparameterized as follows:

$$\| \mathbf{y} - \mathbf{C}\boldsymbol{\alpha} - \tilde{\mathbf{X}}\boldsymbol{\delta} - \tilde{\mathbf{Z}}\mathbf{u} \|^2 + \lambda \| \mathbf{u} \|^2 . \tag{7}$$

Hence, the estimators $\hat{\boldsymbol{\alpha}}, \hat{\boldsymbol{\delta}}$, and $\hat{\mathbf{u}}$ that minimize the PLS criterion in equation 7 are the BLUPs of the following linear mixed model:

$$\mathbf{y} = \mathbf{C}\boldsymbol{\alpha} + \tilde{\mathbf{X}}\boldsymbol{\delta} + \tilde{\mathbf{Z}}\mathbf{u} + \boldsymbol{\epsilon}, \quad \mathrm{Cov}\begin{pmatrix} \mathbf{u} \\ \boldsymbol{\epsilon} \end{pmatrix} = \begin{pmatrix} \sigma_u^2 \mathbf{I}_K & \mathbf{0} \\ \mathbf{0} & \sigma_\varepsilon^2 \mathbf{I}_L, \end{pmatrix} \tag{8}$$

where $L = \sum_{i}^{n} T_i$. The vectors $(\boldsymbol{\alpha}', \delta')'$ and $\mathbf{u}$ represent the fixed effects and random effects of the mixed model, respectively. The smoothing parameter $\lambda$ is the ratio of the variance components, i.e., $\lambda = \sigma_u^2/\sigma_\varepsilon^2$.

With $\hat{\boldsymbol{\beta}} = (\hat{\delta}', \hat{\mathbf{u}}')'$ the estimated smooth function can be obtained as $\hat{\eta}(a) = \boldsymbol{\Phi}_p'(a)\hat{\boldsymbol{\beta}}$. When also taking into account the effects of the covariates in $\mathbf{C}$, the fitted response can be calculated from equation 8, substituting the BLUPs for the unknown parametric and nonparametric components.

Ruppert et al. (2003) show that a pointwise confidence band with bias allowance can be constructed as:

$$\hat{\eta}(a) \pm z_{1-\alpha/2}\hat{\sigma}_\varepsilon \sqrt{(\mathbf{0}_{1\times M}', \boldsymbol{\Phi}_p'(a))(\mathbf{D}'\mathbf{D} + \hat{\lambda}\mathbf{H})^{-1}(\mathbf{0}_{1\times M}', \boldsymbol{\Phi}_p'(a))'}, \tag{9}$$

where $M$ is the number of covariates in the matrix $\mathbf{C}$, and $p$ is the number of basis functions. $\hat{\lambda}$ is calculated using the estimated variance components $\hat{\sigma}_u^2$ and $\hat{\sigma}_\varepsilon^2$. The matrix $\mathbf{D}$ is defined as $\mathbf{D} = (\mathbf{C}, \mathbf{X})$ and:

$$\mathbf{H} = \begin{pmatrix} \mathbf{0}_{M\times M} & \mathbf{0}_{M\times p} \\ \mathbf{0}_{p\times M} & \mathbf{G}_{p\times p} \end{pmatrix}. \tag{10}$$

$z_{1-\alpha/2}$ denotes the $(1-\alpha/2)$-quantile of the standard normal distribution. Therefore, a $(1-\alpha)100\%$ confidence band for the fitted response values can be calculated as:

$$\hat{y} \pm z_{1-\alpha/2}\hat{\sigma}_\varepsilon \sqrt{\mathbf{d}_a'(\mathbf{D}'\mathbf{D} + \hat{\lambda}\mathbf{H})^{-1}\mathbf{d}_a}. \tag{11}$$

The $(p+M)\times 1$ vector $\mathbf{d}_a$ contains average values for the remaining covariates and the truncated power basis for age values $a$ used in the calculation of the interval, i.e., $\mathbf{d}_a = (\overline{\mathbf{c}}', \boldsymbol{\Phi}_p'(a))'$.

In order to take the within subject correlation into account, we apply a generalized P-spline method, i.e., the error sum of squares in the PLS criterion is weighted by the covariance matrix of $\mathbf{y}$, $\boldsymbol{\Omega} = \mathrm{Cov}(\mathbf{y})$. For the implementation, this means that generalized least squares (GLS) transformations of $\mathbf{y}$, $\mathbf{y}^* = \boldsymbol{\Omega}^{-1/2}\mathbf{y}$, and likewise for $\mathbf{C}$ and $\mathbf{X}$ are used in the computation.

Because the covariance matrix $\Omega$ is unknown, it is estimated using the Swamy-Arora method implemented in Stata 10 MP (command -xtreg-) in a first step parametric GLS regression (cf. Swamy and Arora 1972). The model specification includes a third-order polynomial of age (cf. Appendix D). Alternatively, one could incorporate an individual-specific random effect in an additive mixed-model framework because the GLS estimator under the normality assumption is equivalent to the maximum likelihood estimator. However, the GLS transformation has the advantage in practical use that the estimation of the linear mixed model in equation 8 is faster because of the omitted individual specific error term component.

## 5 Data

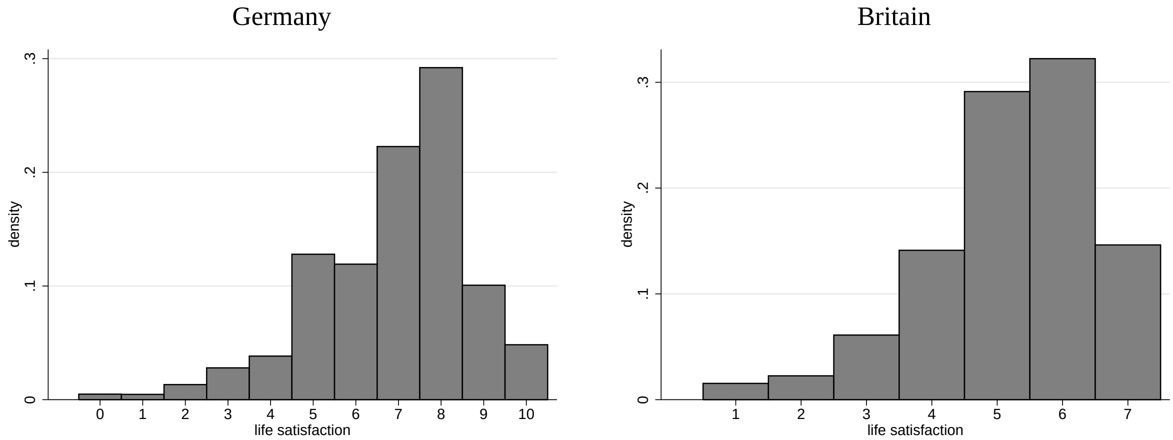
The data used in this paper are based on the British Household Panel Survey (BHPS) and the German Socio-Economic Panel Study (SOEP). Both the BHPS and the SOEP are representative longitudinal studies of households that survey the same respondents annually. The data are highly suitable for the present analysis because questions about well-being are central to these studies (cf. Taylor et al. 2006, Wagner et al. 2007).[1]

In the SOEP, life satisfaction is ascertained by the following question: "How satisfied are you with your life, all things considered?" The response is measured on an 11-point scale ranging from 0 (completely dissatisfied) to 10 (completely satisfied). The distribution of life satisfaction in Germany is shown in Figure 2. The respondents report an average level of 6.9. The median is seven and the most frequent score (mode) in the sample is eight.

The BHPS collects detailed information about how people assess their satisfaction with their lives asking the following question: "How dissatisfied or satisfied are you with your life overall?" Responses are measured on a seven-point scale ranging from 1 (not satisfied at all) to

[1] The data used in this paper are extracted using the add-on package PanelWhiz v2.0 (Nov 2007) for Stata. PanelWhiz was written by Dr. John P. Haisken-DeNew (john@panelwhiz.eu). The PanelWhiz-generated DO file to retrieve the SOEP and BHPS data used here and any PanelWhiz plug-ins are available upon request. Any data or computational errors in this paper are our own. Haisken-DeNew and Hahn (2006) describe PanelWhiz in detail.

**Figure 2**
**Distribution of life satisfaction in Germany and Britain**




*Source*: SOEP 1986-2007 (without 1990, 1993). BHPS 1996-2006 (without 2001).

7 (completely satisfied). The distribution of life satisfaction in Britain is also shown in Figure 2. In Britain, the average level of life satisfaction is 5.2. The median is five and the most frequent score (mode) in the sample is six. Unfortunately, the question regarding people's life satisfaction was not asked in the BHPS before 1996 or in 2001.

Ferrer-i-Carbonell and Frijters (2004) show that assuming ordinality or cardinality of satisfaction scores makes little difference to the results of regression analyses. Hence, we are able to apply econometric models designed for continuous response variables.

In order to disentangle the relationship between subjective well-being and age, it is important to control for further socioeconomic characteristics that are associated with the level of utility. In particular, health status is a well-known determinant of well-being (e.g., Easterlin 2005). Both the SOEP and the BHPS provide information about the respondents' health status. We use the respondents' disability status and the number of nights stayed in hospital in the SOEP data set. These objective health measures are less prone to measurement errors and the issue of endogeneity—problems that may occur using the self-reported health status (cf. Jäckle 2007). Unfortunately, the information about the numbers of nights stayed in hospital is not available for 1990 or 1993 so that we are not able to use the respective waves. In the BHPS, we generate a dummy variable indicating whether a respondent experienced bad health issues resulting from problems with arms, legs, hands, sight, hearing, skin conditions/allergy, chest/breathing, heart/blood pressure, stomach or digestion, diabetes, anxiety, depression, alcohol or drugs, epilepsy, migraine, cancer, stroke and other problems.

Furthermore, we exclude the data collected at the first and second interviews of each person from the SOEP sample because of panel and learning effects (cf. Landua 1993, Ehrhardt et al. 2000). After all, the SOEP sample consists of 20 waves from 1986 to 2007 excluding 1990 and 1993. In contrast, we refrain from excluding observations from the BHPS because the period for which data are available is considerably shorter than in the SOEP, so that our BHPS sample contains observations of 10 waves from 1996 to 2006 excluding 2001 (because of the missing life satisfaction question). The descriptive statistics of the variables used in the analyses can be found in Table 3 in the Appendix.

## 6 Empirical evidence

In this section, the relationship between life satisfaction and age is analyzed using the semiparametric regression approach introduced in Section 4. Subsection 6.1 provides an overview of the different assumptions underlying the four model specifications estimated in this paper. The smooth functions describing the three age stages of life satisfaction over the life span are discussed in Subsection 6.2. The differences between the parametric and semiparametric regressions are examined in Subsection 6.3.

### 6.1 Semiparametric regressions: four models

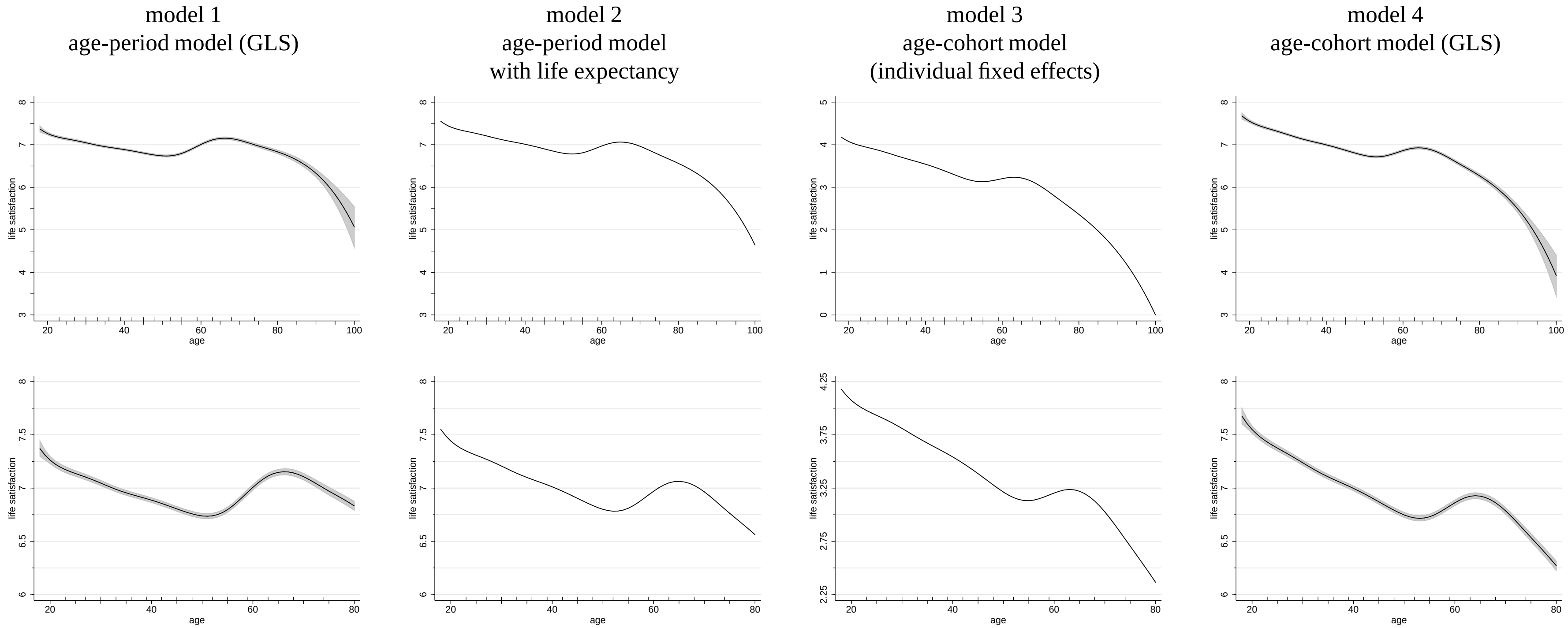
We estimate four semiparametric regression models using P-splines under different assumptions. Figures 3 and 4 show the resulting age profiles for Germany and Britain, respectively. All regressions have in common that the P-spline smoother of the nonparametric component uses a third-degree truncated power basis, i.e., $k = 3$. $K = 15$ knots are used in the spline regression, which is roughly one-fifth of the distinct age groups. The knots are located at the corresponding sample quantiles. All models include standard socioeconomic control variables in the parametric component: sex, marital status, labor force status, health status, household income, and household size. In the Germany sample, the regressions also control for whether the respondent lives in East or West Germany. The estimation results of the parametric components can be found in the Appendix D.

The first model is an age-period model applying a generalized P-spline smoother. In addition to the standard controls, $T-1$ dummy variables capturing the period fixed effects are included. The age-period model uses GLS-transformed data assuming that the unobserved individual heterogeneity in the longitudinal data is uncorrelated with the explanatory variables. We estimate the covariance structure in a first step parametric regression using the Swamy-Arora method. The regression equation includes a third-order polynomial function of age. The variance estimates obtained from the first step regression are used to GLS-transform the data (for details, cf. Appendix C). This procedure is equivalent to estimating an individual-specific random error term component in the linear mixed model. However, the GLS transformation is beneficial because it allows a faster computation of the linear mixed-model representation of the penalized spline.

The second model is the same as the first one, with the exception that the respondents' sex-specific life expectancy at birth is added as an explanatory variable.[2] The life expectancy is based on the number of deceased and living persons in the entire population. This measure reports the average number of years a newborn child is expected to live, and is a highly condensed source of information about the living conditions of the birth cohort. Hence, it may be regarded as a snapshot of the living conditions of the time period in which one is born. We regard this variable as reflecting further substantive information about cohort-specific influences. Because the life expectancy is identical for all respondents belonging to the same birth cohort and sex, we are confronted with the problem that a bias of the standard errors could result from merging

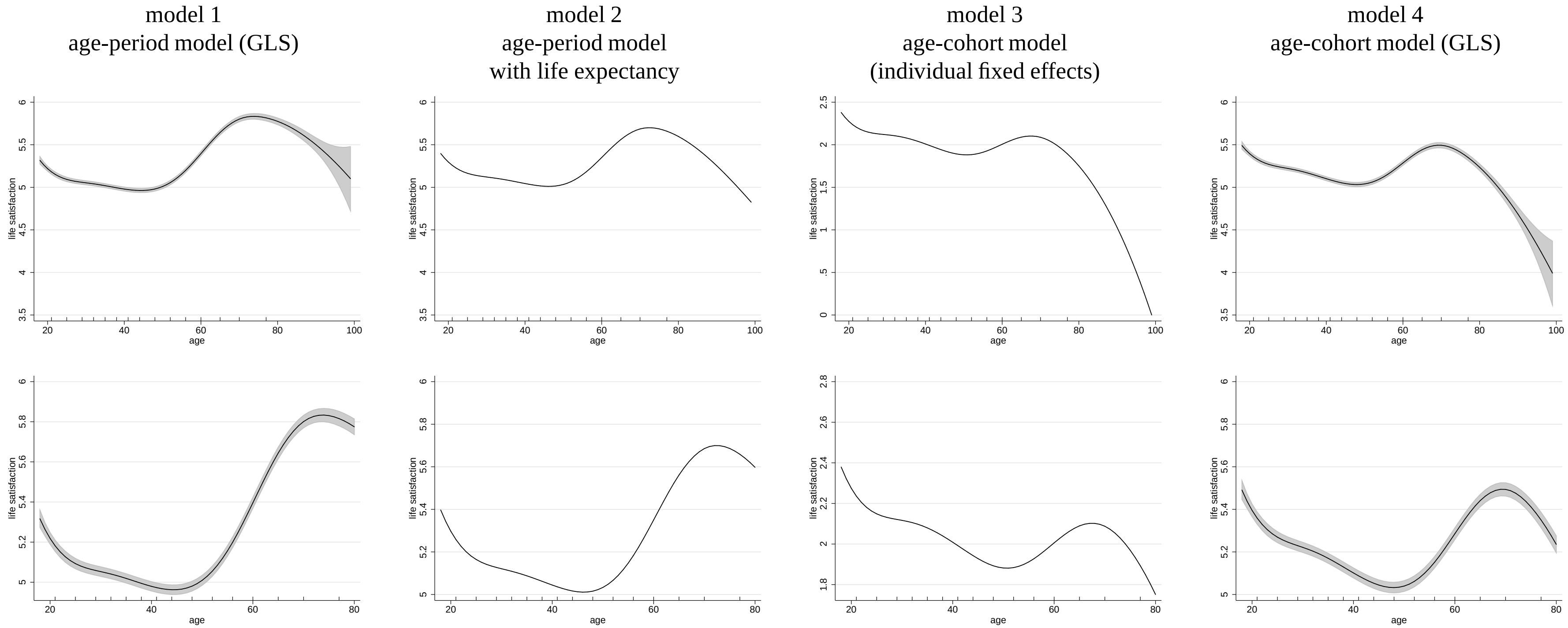
[2] The life expectancy at birth for the British and the German respondents is from the Human Mortality Database, University of California, Berkeley (USA), and the Max Planck Institute for Demographic Research (Germany), available at `www.mortality.org` or `www.humanmortality.de` (data downloaded on 7 March 2009). The data for German birth cohorts born before 1956 are taken from Statistisches Bundesamt (2008).

**Figure 3**
**Life satisfaction over the life span in Germany**




*Note*: The ticks above the x-axes mark the locations of the $K = 15$ knots used in the semiparametric regressions. The shaded areas show 95% confidence bands for the expected value of life satisfaction. Because the calculation of confidence bands is not implemented in the software package we use (Stata 10 MP), we only present confidence bands for the age-period model and the age-cohort model that are based on the GLS-transformed data. The fitted values of the age-cohort individual fixed-effects model cannot be interpreted directly (cf. text).
*Source*: SOEP 1986-2007 (without 1990, 1993)

**Figure 4**
**Life satisfaction over the life span in Britain**




*Note*: The ticks above the x-axes mark the locations of the $K = 15$ knots used in the semiparametric regressions. The shaded areas show 95% confidence bands for the expected value of life satisfaction. Because the calculation of confidence bands is not implemented in the software package we use (Stata 10 MP), we only present confidence bands for the age-period model and the age-cohort model that are based on the GLS-transformed data. The fitted values of the age-cohort individual fixed-effects model cannot be interpreted directly (cf. text).

*Source*: BHPS 1996-2006 (without 2001)

the higher aggregated variable to the micro data (cf. Moulton 1990). Hence, this second estimation does not use GLS-transformed data, but instead the covariance structure is considered by modeling a hierarchical random-error term component: in addition to an individual-specific random effect, a further random term representing the unobserved heterogeneity at the level of the birth cohorts is included in the estimation equations. For convenience, we do not calculate a variability band in this case.

Life expectancy has a highly significant negative impact on life satisfaction, i.e., respondents report lower satisfaction scores when they belong to a cohort characterized by greater life expectancy at birth (cf. Appendix D). In comparison with earlier cohorts, more-recent cohorts of respondents have a higher life expectancy. Hence, this result indicates that the later a person is born, the more dissatisfied he or she is. This finding is likely to reflect that persons belonging to different cohorts have different cohort-specific values and expectations that are more or less met by the circumstances.

The third model is based on an individual-specific fixed-effects model that takes into account the correlation between the individual effect and the covariates. Smoothing is done using demeaned data in the linear mixed-model framework. This procedure implies that the error term variance is underestimated because the individual-specific constants are omitted from the model. Because our interest lies primarily in the shape of the function, we refrain from correcting the bias, and therefore we do not calculate confidence bands in this case either. In addition, because the inference based on the fixed-effects estimator is a conditional inference (in particular, conditional on the individuals in the sample), the fitted values obtained from the fixed-effects model cannot be compared directly with the results obtained from the other models. In particular, the value of the fitted responses on the y-axis cannot be interpreted because of the omitted individual-specific constants. However, an interpretation of the *shape* of the function is possible and provides informative insights. The resulting functional form differs somewhat from the random-effects age-period model.

It must be pointed out that, on the one hand, the fixed-effects estimator implicitly controls for a cohort effect that is included in the individual-specific constant term. On the other hand, the year effects are omitted from this model because it is not possible to estimate a fixed-effects age-period model. The reason for this is that age, period, and cohort effects are indistinguishable and cannot be identified without further assumptions (cf. Section 3). Consequently, we assume that the difference in the shape of the smooth functions arises because we are comparing models with two different model specifications, i.e., an age-period model versus an age-cohort model.

To further confirm our suspicion, we also estimate a random-effects age-cohort model (model 4). The specification includes the year of birth and its square in the regression equation and omits the period dummies. The resulting functional form is close to the fixed-effects age-cohort model. Hence, we conclude that the difference between the random-effects age-period model (model 1) and the fixed-effects age-cohort model (model 3) mirrors the different model specifications: the fixed-effects estimator controls for a cohort effect, whereas the random-effects estimator models period effects.

As already pointed out in Section 3, we believe that the age-period models (model 1 and model 2) are an appropriate choice because the age-cohort regressions do not take into account the impact of macroeconomic variables such as unemployment, inflation, and growth. Their impact can, however, be captured in aggregate by the period dummies in the age-period models.

### 6.2 Three age stages of life satisfaction

The following discussion is primarily based on the evidence provided by model 2 (cf. Appendix D). The regression controls for cohort effects including, in particular, the cohort-specific life expectancy as an explanatory variable. Fixed year effects are also included in the estimation equation. In contrast, the age-cohort models (model 3 and model 4) omit period effects. Instead, they depend on the rather unrealistic assumption that, say, living in 1995 or 2005 makes ceteris paribus no difference to well-being.

In order to control for the effects of panel attrition, we additionally include a set of dummy variables in the regressions indicating whether the respondent leaves the study in one of the subsequent waves. From the estimation results, it is evident that those who leave the sample are clearly less satisfied with their lives compared with those who continue participating. Because one of the major reasons for attrition in our sample is the death of a person, the negative impact may mirror a worsening of the health status, which is not captured by the health indicators.

Despite the differences between the smooth functions obtained from the four model specifications, the graphs in Figures 3 and 4 show a common three-phase pattern describing the course of well-being over the life span.

In the first age stage, the smooth functions indicate a negative, approximately linear trend up to the beginning of the fifth life decade in Germany. Over a period of 35 years, individuals suffer from a decrease in life satisfaction of about 0.7 points on the 11-point scale. The total loss is equivalent to an average annual decline of $0.7/35 = 0.02$ points. In order to compensate for the annual loss in well-being, an increase in income of roughly 4% per year is required, other things being constant (cf. Table 1).[3] For Britain, Figure 4 shows a slightly curved line (i.e., not straight downward) until the respondents almost reach the age of 50. This reduction corresponds to a CIV of 14% each year.

A common explanation of the decline in well-being is that people in this life stage have relatively higher aspirations and expectations that are not met by the circumstances (e.g., Frey and Stutzer 2002). Building on results from research on the psychology of time and aging, we introduce a new possible explanation of the decline in life satisfaction. It is well established in the psychology literature that the perception of time changes as people grow older. An early account comes from the pioneer psychologist William James: "The same space of time seems shorter as we grow older" (James 1981, p. 588). In recent decades, the psychology literature has provided extensive support for the hypothesis that people have the impression that time passes more quickly with advancing age (e.g., Lemlich 1975, Baum et al. 1984, Schroots and Birren 1990, Craik and Hay 1999). The age-induced decrease in metabolism, the general

[3] The calculation of the income variations are based on the age-period model with life expectancy (model 2). In Germany, the effect of the logarithm of household income is estimated to be 0.5. This means that an increase in income of 1% brings an increase in well-being of 0.005 points on the 11-point scale. Hence, a reduction in life satisfaction of 0.02 points requires a compensating income variation (CIV) of 4%. The calculation is identical for Britain.

decline in biological activity, and the slowing of the internal biological clock are possible causes resulting in a change in the perception of time (for an overview, cf. Block et al. 1998). In this context, neuroscientific research provides evidence that aging disrupts memory performance (cf. Anderson et al. 2000).

What are the implications of the fact that subjective time accelerates with aging for the satisfaction scores collected *annually* in the SOEP and the BHPS? Although the wording of the questionnaires does not refer to a particular time period (cf. Section 5), it is plausible to assume that the respondents base their evaluation of their lives over a certain time interval. For example, people may assess their overall well-being in the previous year. The literature cited above suggests that equal-sized real-time intervals are connected to decreasing subjective time intervals because of the perceived acceleration of time. The underlying reasons may also produce an effect on subjective well-being: reduced biological activity and lower episodic memory performance are supposed to lead to a diminution in the number of pleasurable experiences and memories processed. This implies that, from the perspective of an aging individual, fewer events occur within the annual time intervals that are subjectively perceived as becoming shorter over the life span. As a conclusion, we infer that the smaller number of (pleasurable) events and experiences, which are processed in shorter (subjective) time intervals, also produce less satisfaction.

In the second age stage, a restoration effect on satisfaction occurs. The literature labels this phase as the "gerontological paradox" (Herzog and Markus 1999, p. 244). Because this life stage is characterized by multiple losses (e.g., people experience a deterioration of health and functioning, and spouses and friends die), one would actually expect happiness to decline because of the deterioration of objective conditions. However, individuals exhibit increasing life satisfaction in this age stage. Several reasons could account for this phenomenon. First, rising levels of financial satisfaction, satisfaction with material needs, and satisfaction with human relationships may contribute to an increase in overall life satisfaction (cf. Diener and Suh 1997, Easterlin 2006). A second reason for the increase in satisfaction is supposed to result from adaptation: people lower their expectations and adjust their life goals to their circumstances (cf. Campbell et al. 1976). Third, people may derive pleasure from anticipating retirement: it seems reasonable to assume that approximately 10 years before retirement people develop more concrete expectations about how they wish to spend their time and that this planning process may induce eager anticipation.

Although an upward trend is clearly seen in both data sets, differences exist between Germany and Britain (cf. Table 1): in Germany, life satisfaction increases over a period of about 13 years by approximately 0.3 points on the 11-point scale. In contrast, the increase in Britain is more sustainable. The British respondents improve their life satisfaction by about 0.7 on the seven-point scale over a period of approximately 22 years. The compensating income variations indicate that the annual positive effect in the second age stage is equal to an increase in income of roughly 5% per year for the German respondents. A considerably higher value is obtained for the British respondents: the increase in life satisfaction is worth an increase in income of 35% per year. Not only does model 2, on which this calculation is based, indicate a stronger increase in well-being in Britain, but also all three remaining models point to a more sustainable restoration effect in the British data. However, because the satisfaction scales in the SOEP and the BHPS are not comparable directly, and considerably different effects of income on well-being are estimated for both countries, this comparison should be read with caution.

In the third phase, persons over the age of 65 again experience a substantial decline in life satisfaction. We suspect that this life stage is characterized by various events and processes that are not captured by the control variables and that may cause the deterioration in well-being. In particular, the decline in satisfaction in the old age stage may be attributed to health issues that are not fully expressed by the rudimentary health indicators used in the regressions. In the context of the state of health, age may capture the effects of terminal decline, i.e., the decline in cognitive abilities while people stay physically healthy. Therefore, Mroczek and Spiro (2005) assume that "certain psychological constructs, such as cognitive function or subjective life satisfaction, may be more sensitive indicators of serious underlying medical problems than are traditional physiological variables such as blood pressure" (p. 198). Until the age of 80, the SOEP respondents suffer from a loss in well-being that amounts to 0.5 points on the 11-point scale. Because the decline starts about five years later in Britain, the BHPS respondents experience a reduction in life satisfaction of only approximately 0.1 points (on the seven-point scale)

**Table 1**
**Three age stages of life satisfaction**

| stage | age min | age max | Δ age | Δ LS | Δ LS p.a. | CIV |
|---|---|---|---|---|---|---|
| Germany (11-point scale) | | | | | | |
| 1 | 18 | 52 | 35 | -0.7 | -0.020 | 4.0% |
| 2 | 53 | 65 | 13 | 0.3 | 0.023 | -4.6% |
| 3 | 66 | 80 | 15 | -0.5 | -0.033 | 6.7% |
| Britain (seven-point scale) | | | | | | |
| 1 | 18 | 48 | 31 | -0.4 | -0.013 | 14.3% |
| 2 | 49 | 70 | 22 | 0.7 | 0.032 | -35.4% |
| 3 | 71 | 80 | 10 | -0.1 | -0.010 | 11.1% |

*Note*: The calculations are based on the estimation results for model 2 (age-period model with life expectancy). The coefficient of the logarithm of household income is estimated to be 0.5 for Germany and 0.09 for Britain. Estimation results can be found in Tables 7 and 8 in the Appendix. Δ LS denotes the change in life satisfaction over the whole duration of the life stage. CIV is the compensating income variation required in each year to compensate for the decrease/increase in life satisfaction per annum.

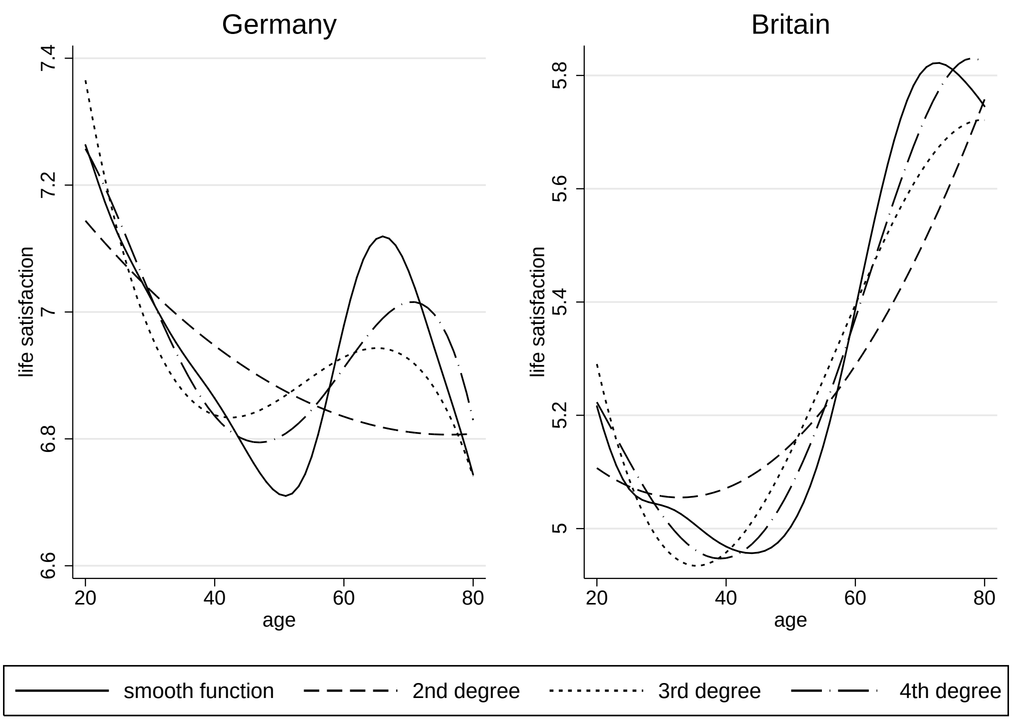
over a period of about 10 years. The numbers are equivalent to an annual CIV of 7% and 11% in Germany and Britain, respectively.

### 6.3 Parametric versus semiparametric regression results

The U-shaped well-being profile frequently found in the econometrics literature obviously provides only an incomplete picture of the course of subjective well-being over the life span—although the smoothing curves presented in this paper show that satisfaction declines with advancing age, and then rises after well-being has reached a minimum. However, the quadratic model does not depict the age profile correctly because it ignores the second turning point and the downward trend in satisfaction in the third age stage. Particularly for Germany, the U-shaped profile is misleading: the minimum of life satisfaction is located where it is actually maximal (cf. Figure 5). Therefore, we propose to include at least one additional polynomial (i.e., a cubic term of age) to capture the second turning point toward the end of life.

Figure 5 shows the course of life satisfaction over the life span obtained from polynomial functions of the third and fourth degree that are able to capture the second turning point. The

**Figure 5**
**Polynomial vs. semiparametric regressions**




*Note*: Age-period models.
*Source*: SOEP 1986-2007 (without 1990, 1993), BHPS 1996–2006 (without 1999 and 2001).

functions are obtained from age-period models including the standard socioeconomic control variables (cf. Section 6.1) and omitting life expectancy. However, the polynomial functions also describe the relationship between subjective well-being and age imprecisely. This can be followed by a comparison with the results obtained from the semiparametric regressions in Section 6.1.

A comparison of the semiparametric and the parametric regressions reveals two noteworthy findings that hold for both Britain and Germany. First, the polynomial specifications estimate the minimum in midlife earlier than it is observed in the semiparametric regression. Second, the maximum derived from the higher-order polynomial parametric regressions is located at a higher age. (The third-order polynomial for the Germany data is the only exception because its maximum corresponds to the maximum indicated by the smooth function.) To sum up, Figure 5 shows clearly that neither the third- nor the fourth-order polynomial parametric regressions identify the minimum or maximum of life satisfaction in the data exactly. Polynomials cannot reproduce the sharp increase in life satisfaction in the second age stage.

## 7 Conclusion

The present paper analyzed the relationship between life satisfaction and age using semiparametric regression models using P-splines. Splines have, compared with parametric polynomial curves, the advantage that they do not require a priori assumptions about the underlying functional form. This approach allowed us to critically reassess the U-shaped profile frequently reported in the economics literature on subjective well-being. Our conclusion is that the U-shaped profile is only half the truth. The other half is that satisfaction has a second turning point later in life, after which well-being declines. Furthermore, the analysis clearly shows that polynomial functions of third or fourth order provide only an incomplete picture of the path of satisfaction over the life span: although they showed the second turning point, the minimum and maximum points are located inaccurately.

Using data from the BHPS and the SOEP, we inferred that there is a universal three-phase pattern of life satisfaction. In the first age stage, well-being gradually declines over a period of 30 to 35 years. Particularly in Germany, the downward trend has a quite regular shape. This leads us to a new possible explanation of the process: evidence from the psychology literature suggests that a reduction in biological and episodic memory performance alters the perception of time. People perceive the pace of time to speed up with advancing age. The reduction in the number of pleasurable events processed in subjectively shortening time intervals could be held responsible, among other things, for the steady decline in well-being. To the best of our knowledge, this argument has not been put forward in the economic well-being literature yet.

In the second age stage, well-being takes a turn for the better and increases considerably. This restoration effect is more distinctive for Britain than for Germany. Although we refrained from directly comparing the British and the German numbers (which is particularly difficult because of the different response scales), we nevertheless find a significant difference: the empirical evidence suggests that, assuming a life expectancy of 80 years, the British experience an improvement in their well-being over their life span. In contrast, the German respondents end up less satisfied in the third age stage compared with the first age stage. The upward trend is supposed to result from changing domain satisfactions as well as adaptive processes. The third age-phase is characterized by declining satisfaction again, which may be attributable to otherwise unobserved health problems and the effects of impending death.

The discussion of the indistinguishability of age, period, and cohort effects led to the conclusion that one has to question the substantive information that is represented by these variables, rather than to search for a solution using reparameterizations of the linear age-period-cohort model that are based on more or less plausible identification restrictions. Therefore, researchers are better advised to solve the indistinguishability problem by explicating the underlying mechanisms. In the context of the research question of the present paper, we attempted to solve the task of identification by including substantive variables in the regression. In particular, the impact of life expectancy turned out to have a negative impact on life satisfaction. This finding gives rise to the supposition that individuals born in the early 20th century (when life expectancy was lower) are more satisfied with their lives than those born later. Hence, the members of earlier birth cohorts (e.g., individuals who socialized during the period of World Wars I and II) may have lower expectations that are more likely to be met by their circumstances. However, with respect to the underlying mechanisms of the cohort effect, our study raises more questions than it answers so that further research is required on this topic.

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## A Descriptive statistics

**Table 2**
**Summary statistics (SOEP)**

| Variable | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|
| life satisfaction | 6.908 | 1.812 | 0 | 10 |
| age | 46.692 | 16.635 | 18 | 100 |
| disability status: disabled | 0.108 | 0.31 | 0 | 1 |
| nights stayed in hospital | 1.851 | 8.965 | 0 | 365 |
| years of education | 11.545 | 2.570 | 7 | 18 |
| log of net household income | 7.974 | 0.577 | 4.605 | 11.513 |
| log of household size | 0.937 | 0.496 | 0 | 2.833 |
| sex: female | 0.516 | 0.5 | 0 | 1 |
| German | 0.835 | 0.371 | 0 | 1 |
| full time employed | 0.443 | 0.497 | 0 | 1 |
| part time employed | 0.122 | 0.327 | 0 | 1 |
| non-working | 0.435 | 0.496 | 0 | 1 |
| unemployed | 0.070 | 0.255 | 0 | 1 |
| married | 0.670 | 0.470 | 0 | 1 |
| single | 0.196 | 0.397 | 0 | 1 |
| divorced | 0.068 | 0.251 | 0 | 1 |
| widowed | 0.066 | 0.248 | 0 | 1 |
| West-Germany | 0.777 | 0.416 | 0 | 1 |
| life expectancy | 65.325 | 6.580 | 37.17 | 78.94 |
| 1986 | 0.036 | 0.187 | 0 | 1 |
| 1987 | 0.036 | 0.186 | 0 | 1 |
| 1988 | 0.035 | 0.183 | 0 | 1 |
| 1989 | 0.034 | 0.181 | 0 | 1 |
| 1991 | 0.033 | 0.178 | 0 | 1 |
| 1992 | 0.047 | 0.211 | 0 | 1 |
| 1994 | 0.045 | 0.207 | 0 | 1 |
| 1995 | 0.044 | 0.204 | 0 | 1 |
| 1996 | 0.045 | 0.207 | 0 | 1 |
| 1997 | 0.046 | 0.210 | 0 | 1 |
| 1998 | 0.044 | 0.205 | 0 | 1 |
| 1999 | 0.043 | 0.203 | 0 | 1 |
| 2000 | 0.047 | 0.212 | 0 | 1 |
| 2001 | 0.045 | 0.208 | 0 | 1 |
| 2002 | 0.072 | 0.258 | 0 | 1 |
| 2003 | 0.070 | 0.255 | 0 | 1 |
| 2004 | 0.074 | 0.262 | 0 | 1 |
| 2005 | 0.072 | 0.258 | 0 | 1 |
| 2006 | 0.068 | 0.252 | 0 | 1 |
| 2007 | 0.065 | 0.247 | 0 | 1 |

*Source*: SOEP 1986-2007 (without 1990, 1993). $nT = 253044$, $n = 33451$.

**Table 3**
**Summary statistics (BHPS)**

| Variable | Mean | Std. Dev. | Min. | Max. |
|---|---|---|---|---|
| satisfaction with life | 5.223 | 1.300 | 1 | 7 |
| age | 46.617 | 17.910 | 18 | 99 |
| log of net household income | 7.573 | 0.765 | 3.912 | 11.197 |
| log of household size | 0.912 | 0.509 | 0 | 2.639 |
| sex: female | 0.546 | 0.498 | 0 | 1 |
| health problems | 0.608 | 0.488 | 0 | 1 |
| education: low | 0.232 | 0.422 | 0 | 1 |
| education: mid | 0.393 | 0.488 | 0 | 1 |
| education: high | 0.375 | 0.484 | 0 | 1 |
| in school | 0.036 | 0.186 | 0 | 1 |
| (self-)employed | 0.596 | 0.491 | 0 | 1 |
| unemployed | 0.032 | 0.177 | 0 | 1 |
| retired | 0.004 | 0.066 | 0 | 1 |
| non working | 0.128 | 0.334 | 0 | 1 |
| married | 0.553 | 0.497 | 0 | 1 |
| coupled | 0.117 | 0.321 | 0 | 1 |
| widowed | 0.076 | 0.266 | 0 | 1 |
| divorced | 0.057 | 0.233 | 0 | 1 |
| separated | 0.018 | 0.133 | 0 | 1 |
| single | 0.179 | 0.383 | 0 | 1 |
| life expectancy | 68.210 | 6.475 | 33.38 | 78.23 |
| 1996 | 0.069 | 0.254 | 0 | 1 |
| 1997 | 0.081 | 0.274 | 0 | 1 |
| 1998 | 0.080 | 0.271 | 0 | 1 |
| 1999 | 0.113 | 0.317 | 0 | 1 |
| 2000 | 0.112 | 0.315 | 0 | 1 |
| 2002 | 0.115 | 0.320 | 0 | 1 |
| 2003 | 0.112 | 0.316 | 0 | 1 |
| 2004 | 0.108 | 0.310 | 0 | 1 |
| 2005 | 0.106 | 0.308 | 0 | 1 |
| 2006 | 0.104 | 0.305 | 0 | 1 |

*Source*: BHPS 1996-2006 (without 2001). $nT = 123656$, $n = 23785$.

## B Estimation results: identification problem of the fixed effects estimator

**Table 4**
**Estimation results: life satisfaction**

| Variable | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| age | -0.130*** | -0.085*** | -0.009* | -0.026*** |
| | (0.010) | (0.007) | (0.005) | (0.003) |
| age squared/1000 | -0.169*** | -0.169*** | -0.169*** | -0.169*** |
| | (0.024) | (0.024) | (0.024) | (0.024) |
| disability status: disabled | -0.259*** | -0.259*** | -0.259*** | -0.259*** |
| | (0.017) | (0.017) | (0.017) | (0.017) |
| nights stayed in hospital | -0.011*** | -0.011*** | -0.011*** | -0.011*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| years of education | 0.005 | 0.005 | 0.005 | 0.005 |
| | (0.004) | (0.004) | (0.004) | (0.004) |
| log of net household income | 0.390*** | 0.390*** | 0.390*** | 0.390*** |
| | (0.011) | (0.011) | (0.011) | (0.011) |
| log of household size | -0.196*** | -0.196*** | -0.196*** | -0.196*** |
| | (0.013) | (0.013) | (0.013) | (0.013) |
| full time employed | 0.011 | 0.011 | 0.011 | 0.011 |
| | (0.012) | (0.012) | (0.012) | (0.012) |
| part time employed | -0.049*** | -0.049*** | -0.049*** | -0.049*** |
| | (0.013) | (0.013) | (0.013) | (0.013) |
| unemployed | -0.593*** | -0.593*** | -0.593*** | -0.593*** |
| | (0.014) | (0.014) | (0.014) | (0.014) |
| single | -0.146*** | -0.146*** | -0.146*** | -0.146*** |
| | (0.020) | (0.020) | (0.020) | (0.020) |
| divorced | -0.024 | -0.024 | -0.024 | -0.024 |
| | (0.022) | (0.022) | (0.022) | (0.022) |
| widowed | -0.332*** | -0.332*** | -0.332*** | -0.332*** |
| | (0.029) | (0.029) | (0.029) | (0.029) |
| West-Germany | 0.218*** | 0.218*** | 0.218*** | 0.218*** |
| | (0.044) | (0.044) | (0.044) | (0.044) |
| fixed year effects: reference 1986 | | | | |
| additionally omitted year dummy | 1988 | 1989 | 1991 | 2004 |

*Note*: Significance levels: *<0.1, *<0.05, ***<0.01.
*Source*: SOEP 1986-2007 (without 1990, 1993). $nT = 253044$, $n = 33451$.

**Table 5**
**Estimation results: financial satisfaction**

| Variable | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| age | -0.085*** | -0.034*** | -0.099*** | -0.022*** |
| | (0.012) | (0.006) | (0.004) | (0.003) |
| age squared/1000 | 0.371*** | 0.371*** | 0.371*** | 0.371*** |
| | (0.027) | (0.027) | (0.027) | (0.027) |
| disability status: disabled | -0.072*** | -0.072*** | -0.072*** | -0.072*** |
| | (0.019) | (0.019) | (0.019) | (0.019) |
| nights stayed in hospital | -0.001*** | -0.001*** | -0.001*** | -0.001*** |
| | (0.000) | (0.000) | (0.000) | (0.000) |
| years of education | 0.004 | 0.004 | 0.004 | 0.004 |
| | (0.005) | (0.005) | (0.005) | (0.005) |
| log of net household income | 1.419*** | 1.419*** | 1.419*** | 1.419*** |
| | (0.013) | (0.013) | (0.013) | (0.013) |
| log of household size | -0.550*** | -0.550*** | -0.550*** | -0.550*** |
| | (0.016) | (0.016) | (0.016) | (0.016) |
| full time employed | 0.293*** | 0.293*** | 0.293*** | 0.293*** |
| | (0.013) | (0.013) | (0.013) | (0.013) |
| part time employed | 0.031** | 0.031** | 0.031** | 0.031** |
| | (0.015) | (0.015) | (0.015) | (0.015) |
| unemployed | -0.698*** | -0.698*** | -0.698*** | -0.698*** |
| | (0.017) | (0.017) | (0.017) | (0.017) |
| single | -0.308*** | -0.308*** | -0.308*** | -0.308*** |
| | (0.023) | (0.023) | (0.023) | (0.023) |
| divorced | -0.185*** | -0.185*** | -0.185*** | -0.185*** |
| | (0.025) | (0.025) | (0.025) | (0.025) |
| widowed | 0.080** | 0.080** | 0.080** | 0.080** |
| | (0.033) | (0.033) | (0.033) | (0.033) |
| West-Germany | 0.397*** | 0.397*** | 0.397*** | 0.397*** |
| | (0.051) | (0.051) | (0.051) | (0.051) |
| fixed year effects: reference 1986 | | | | |
| additionally omitted year dummy | 1988 | 1991 | 1995 | 2002 |

*Note*: Significance levels: *<0.1, *<0.05, ***<0.01.
*Source*: SOEP 1986-2007 (without 1990, 1993). $nT = 250366$, $n = 33320$.

## C GLS transformation

The covariance structure of the longitudinal data is estimated using the Swamy-Arora method implemented in the Stata 10 as the command -xtreg-. The GLS transformation of each element $z$ in $\mathbf{y}, \mathbf{C}, \mathbf{X}$ is:

$$z^*_{it} = z_{it} - \theta_i \bar{z}_{i\cdot} \tag{12}$$

where $\bar{z}_{i\cdot} = (1/T)\sum_i^{T_i} z_{it}$ and

$$\theta_i = 1 - \sqrt{\frac{\sigma^2_\varepsilon}{\sigma^2_\varepsilon + T_i \sigma^2_\alpha}}. \tag{13}$$

**Table 6**
**Estimation results: first step regression (random effects model)**

| Variable | coefficient | s.e. |
|---|---|---|
| age | -0.143*** | (0.006) |
| age squared/$10^2$ | 0.275*** | (0.012) |
| age cubed/$10^3$ | -0.017*** | (0.001) |
| sex: female | 0.064*** | (0.015) |
| disability status: disabled | -0.445*** | (0.014) |
| nights stayed in hospital | -0.012*** | (0.000) |
| years of education | 0.039*** | (0.002) |
| log of net household income | 0.474*** | (0.009) |
| log of household size | -0.220*** | (0.012) |
| German | 0.043** | (0.020) |
| full time employed | 0.028*** | (0.011) |
| part time employed | -0.015 | (0.012) |
| unemployed | -0.640*** | (0.014) |
| single | -0.219*** | (0.016) |
| divorced | -0.158*** | (0.018) |
| widowed | -0.215*** | (0.023) |
| West-Germany | 0.513*** | (0.017) |
| attrition in 1 | -0.388*** | (0.019) |
| attrition in 2 | -0.271*** | (0.016) |
| attrition in 3 | -0.182*** | (0.017) |
| attrition in 4 | -0.136*** | (0.018) |
| attrition in 5 | -0.086*** | (0.019) |
| attrition in 6 | -0.053*** | (0.020) |
| 1987 | -0.175*** | (0.019) |
| 1988 | -0.245*** | (0.020) |
| 1989 | -0.246*** | (0.020) |
| 1991 | -0.046** | (0.020) |
| 1992 | -0.263*** | (0.019) |
| 1994 | -0.386*** | (0.020) |
| 1995 | -0.371*** | (0.020) |
| 1996 | -0.378*** | (0.020) |
| 1997 | -0.498*** | (0.020) |
| 1998 | -0.420*** | (0.020) |
| 1999 | -0.383*** | (0.020) |
| 2000 | -0.440*** | (0.020) |
| 2001 | -0.413*** | (0.021) |
| 2002 | -0.223*** | (0.019) |
| 2003 | -0.284*** | (0.019) |
| 2004 | -0.447*** | (0.019) |
| 2005 | -0.325*** | (0.019) |
| 2006 | -0.429*** | (0.020) |
| 2007 | -0.399*** | (0.020) |
| constant | 5.305*** | (0.117) |
| $\sigma_\alpha$ | 1.131 | |
| $\sigma_\varepsilon$ | 1.295 | |

*Note*: Significance levels: *<0.1, *<0.05, ***<0.01. Reference year: 1986.
*Source*: SOEP 1986-2007 (without 1990, 1993). $nT = 253044$, $n = 33451$.

# D Estimation results: parametric components

**Table 7**
**Results for parametric components (SOEP)**

| | model 1 | | model 2 | | model 3 | | model 4 | |
|---|---|---|---|---|---|---|---|---|
| | age-period | | age-period | | age-cohort | | age-cohort | |
| Variable | coef. | s.e. | coef. | s.e. | coef. | s.e. | coef. | s.e. |
| sex: female | 0.074*** | (0.015) | 0.396*** | (0.033) | — | | 0.071*** | (0.015) |
| disability status: disabled | -0.449*** | (0.014) | -0.453*** | (0.014) | -0.272*** | (0.015) | -0.446*** | (0.014) |
| nights stayed in hospital | -0.012*** | (0.000) | -0.012*** | (0.000) | -0.010*** | (0.000) | -0.012*** | (0.000) |
| years of education | 0.033*** | (0.002) | 0.033*** | (0.002) | 0.007* | (0.004) | 0.039*** | (0.002) |
| log of net household income | 0.491*** | (0.010) | 0.494*** | (0.010) | 0.316*** | (0.008) | 0.389*** | (0.008) |
| log of household size | -0.196*** | (0.012) | -0.197*** | (0.012) | -0.114*** | (0.012) | -0.138*** | (0.012) |
| German | 0.046** | (0.020) | 0.029 | (0.020) | — | | 0.036* | (0.020) |
| full time employed | 0.079*** | (0.011) | 0.086*** | (0.011) | 0.131*** | (0.011) | 0.109*** | (0.011) |
| part time employed | 0.019 | (0.012) | 0.018 | (0.012) | 0.022* | (0.012) | 0.033*** | (0.012) |
| unemployed | -0.597*** | (0.014) | -0.594*** | (0.014) | -0.534*** | (0.014) | -0.608*** | (0.014) |
| single | -0.176*** | (0.017) | -0.200*** | (0.017) | -0.175*** | (0.019) | -0.205*** | (0.017) |
| divorced | -0.137*** | (0.018) | -0.132*** | (0.018) | -0.010 | (0.020) | -0.143*** | (0.018) |
| widowed | -0.195*** | (0.023) | -0.193*** | (0.023) | -0.274*** | (0.027) | -0.225*** | (0.023) |
| West-Germany | 0.509*** | (0.017) | 0.505*** | (0.016) | 0.251*** | (0.041) | 0.550*** | (0.016) |
| attrition in 1 | -0.381*** | (0.019) | -0.385*** | (0.019) | -0.349*** | (0.021) | -0.411*** | (0.018) |
| attrition in 2 | -0.267*** | (0.016) | -0.272*** | (0.016) | -0.218*** | (0.018) | -0.295*** | (0.016) |
| attrition in 3 | -0.178*** | (0.017) | -0.182*** | (0.017) | -0.107*** | (0.018) | -0.187*** | (0.017) |
| attrition in 4 | -0.132*** | (0.018) | -0.136*** | (0.018) | -0.064*** | (0.018) | -0.147*** | (0.017) |
| attrition in 5 | -0.082*** | (0.019) | -0.085*** | (0.019) | -0.037** | (0.019) | -0.120*** | (0.019) |
| attrition in 6 | -0.050** | (0.020) | -0.053*** | (0.020) | -0.019 | (0.019) | -0.093*** | (0.020) |
| life expectation | — | | -0.042*** | (0.004) | — | | — | |
| cohort | — | | — | | — | | -0.061*** | (0.003) |
| cohort squared | — | | — | | — | | 0.000*** | (0.000) |
| 1987 | -0.175*** | (0.019) | -0.159*** | (0.020) | — | | — | |
| 1988 | -0.245*** | (0.020) | -0.213*** | (0.020) | — | | — | |
| 1989 | -0.247*** | (0.020) | -0.200*** | (0.021) | — | | — | |
| 1991 | -0.051** | (0.020) | 0.026 | (0.022) | — | | — | |
| 1992 | -0.269*** | (0.019) | -0.176*** | (0.021) | — | | — | |
| 1994 | -0.394*** | (0.020) | -0.272*** | (0.023) | — | | — | |
| 1995 | -0.381*** | (0.020) | -0.244*** | (0.024) | — | | — | |
| 1996 | -0.389*** | (0.020) | -0.237*** | (0.025) | — | | — | |
| 1997 | -0.511*** | (0.020) | -0.343*** | (0.026) | — | | — | |
| 1998 | -0.433*** | (0.020) | -0.251*** | (0.027) | — | | — | |
| 1999 | -0.397*** | (0.020) | -0.201*** | (0.028) | — | | — | |
| 2000 | -0.453*** | (0.020) | -0.243*** | (0.029) | — | | — | |
| 2001 | -0.427*** | (0.021) | -0.202*** | (0.031) | — | | — | |
| 2002 | -0.226*** | (0.019) | 0.017 | (0.031) | — | | — | |
| 2003 | -0.288*** | (0.019) | -0.030 | (0.032) | — | | — | |
| 2004 | -0.449*** | (0.019) | -0.176*** | (0.033) | — | | — | |
| 2005 | -0.325*** | (0.019) | -0.038 | (0.035) | — | | — | |
| 2006 | -0.429*** | (0.020) | -0.127*** | (0.036) | — | | — | |
| 2007 | -0.398*** | (0.020) | -0.083** | (0.037) | — | | — | |
| constant | 9.398*** | (3.291) | 12.695*** | (3.355) | — | | 12.246*** | (3.360) |

*Note*: Significance levels: *<0.1, *<0.05, ***<0.01.
*Source*: SOEP 1986-2007 (without 1990, 1993).

**Table 8**
**Results for parametric components (BHPS)**

| | model 1 | | model 2 | | model 3 | | model 4 | |
|---|---|---|---|---|---|---|---|---|
| | age-period | | age-period | | age-cohort | | age-cohort | |
| Variable | coef. | s.e. | coef. | s.e. | coef. | s.e. | coef. | s.e. |
| log of household income | 0.077*** | (0.007) | 0.077*** | (0.007) | 0.045*** | (0.007) | 0.077*** | (0.007) |
| log of household size | -0.087*** | (0.012) | -0.086*** | (0.012) | -0.096*** | (0.013) | -0.090*** | (0.012) |
| sex: female | 0.072*** | (0.013) | 0.162*** | (0.028) | — | | 0.070*** | (0.013) |
| health status: bad | -0.245*** | (0.008) | -0.245*** | (0.008) | -0.148*** | (0.008) | -0.243*** | (0.008) |
| education: middle | 0.016 | (0.017) | 0.022 | (0.017) | 0.013 | (0.037) | 0.030* | (0.017) |
| education: high | 0.034* | (0.017) | 0.036** | (0.017) | 0.048 | (0.036) | 0.038** | (0.017) |
| in training | 0.325*** | (0.024) | 0.324*** | (0.024) | 0.218*** | (0.025) | 0.320*** | (0.024) |
| employed | 0.241*** | (0.012) | 0.242*** | (0.012) | 0.149*** | (0.013) | 0.240*** | (0.012) |
| unemployed | -0.132*** | (0.020) | -0.131*** | (0.020) | -0.149*** | (0.019) | -0.132*** | (0.020) |
| retired | 0.461*** | (0.044) | 0.459*** | (0.044) | 0.372*** | (0.040) | 0.456*** | (0.044) |
| living as couple | -0.051*** | (0.015) | -0.053*** | (0.015) | 0.030* | (0.016) | -0.057*** | (0.015) |
| widowed | -0.323*** | (0.023) | -0.326*** | (0.023) | -0.307*** | (0.028) | -0.337*** | (0.023) |
| divorced | -0.438*** | (0.021) | -0.436*** | (0.021) | -0.230*** | (0.025) | -0.436*** | (0.021) |
| separated | -0.566*** | (0.027) | -0.565*** | (0.027) | -0.428*** | (0.027) | -0.567*** | (0.027) |
| never married | -0.261*** | (0.017) | -0.265*** | (0.017) | -0.130*** | (0.022) | -0.276*** | (0.017) |
| attrition in 1 | -0.090*** | (0.012) | -0.090*** | (0.012) | 0.007 | (0.008) | -0.011 | (0.008) |
| attrition in 2 | -0.073** | (0.030) | -0.074** | (0.030) | -0.021** | (0.010) | -0.033*** | (0.010) |
| attrition in 3 | 0.013 | (0.031) | 0.014 | (0.031) | -0.045*** | (0.008) | -0.048*** | (0.008) |
| life expectation | — | | -0.015*** | (0.004) | — | | — | |
| cohort | — | | — | | — | | -0.043*** | (0.003) |
| cohort squared | — | | — | | — | | 0.000*** | (0.000) |
| 1997 | 0.003 | (0.014) | 0.007 | (0.014) | — | | — | |
| 1998 | 0.073*** | (0.014) | 0.080*** | (0.014) | — | | — | |
| 1999 | -0.075** | (0.033) | -0.064* | (0.034) | — | | — | |
| 2000 | -0.094*** | (0.013) | -0.079*** | (0.014) | — | | — | |
| 2002 | -0.046*** | (0.013) | -0.023 | (0.015) | — | | — | |
| 2003 | -0.038*** | (0.013) | -0.011 | (0.016) | — | | — | |
| 2004 | -0.091*** | (0.014) | -0.061*** | (0.017) | — | | — | |
| 2005 | -0.124*** | (0.018) | -0.089*** | (0.021) | — | | — | |
| 2006 | -0.000 | (0.020) | 0.039* | (0.024) | — | | — | |
| constant | 8.293*** | (1.490) | 9.326*** | (1.461) | — | | 9.679*** | (1.475) |

*Note*: Significance levels: *<0.1, *<0.05, ***<0.01.
*Source*: BHPS 1996-2006 (without 2001).