Do early-life and contemporaneous macro-conditions explain health at older ages? An application to Dutch trends in functional limitations.

France Portrait*
Rob Alessie †
Dorly Deeg ‡ §

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*Institute for Health Sciences, Vrije Universiteit and Tinbergen Institute
†Utrecht school of Economics, Utrecht University; Netspar and Tinbergen Institute
‡Longitudinal Aging Study Amsterdam, Institute for Research in Extramural Medicine, Vrije Universiteit Medical Center
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Address for correspondence: F. Portrait, Institute of Health Sciences, FALW, room U451, De Boelelaan 1085, 1081 HV Amsterdam, The Netherlands.
Tel: 00-31-205982545
Email: france.portrait@falw.vu.nl

Abstract

Understanding health trends is crucial to assess future prevalence of health disorders and for the design of efficient health policies. The paper presents an approach to thoroughly assess the role of early life and contemporaneous macro conditions in explaining health trends later in life. In particular, we investigate the role of exposure to infectious diseases and economic conditions during infancy and childhood, as well as the effect of current health care facilities. Specific attention is paid to the impact of omitted relevant variables, unobserved heterogeneity and to selective attrition. We apply our approach to recent Dutch trends in functional limitations at older ages. Our analyses are performed using data from the Longitudinal Aging Study Amsterdam. The prevalence of functional limitations is found to increase in the nineteen-nineties, in part due to restricted access to health care services.

Key words: early life macro determinants, contemporaneous macro determinants, Trends in Functional limitations, Aging.

1 Introduction

Understanding health trends at older ages is crucial to assess future prevalence of health disorders and future use of health care services. It may also help the design of efficient health policies (see Almond 2002 for a detailed discussion on policy implications).

Health at advanced ages results from the genetic endowment and from a large set of factors across the course of life. Recent research has demonstrated the important role of environmental factors early in life (see Doblhammer 2004 for a recent review). For instance, individuals who faced during pregnancy or the first years of life adverse conditions when it comes to nutrition and disease exposure are found to experience worse health conditions and higher mortality rates at older ages (e.g. Fridlizius 1989, Barker 1998, Roseboom 2001, Fogel 2004, Almond 2006). Furthermore, being born in a recession increases on average the mortality rates later in life (van den Berg, Lindeboom, Portrait 2006). On the other hand, contemporaneous conditions with respect to, e.g., the quality and access to health care, the availability of new medicines or the current economic conditions most likely affect health status (see for example Mackenbach 1996 or Van den Berg et al. 2006). Finally, health at advanced ages is largely affected by the person-specific characteristics, such as age, gender, socio-economic status, lifestyle, parental background, and the health shocks experienced across the course of life (e.g. van den Berg, Lindeboom, Portrait 2003).

Clearly, given the immense number of plausible factors affecting health during lifetime, some relevant information may be missing. In particular, studies on health trends at older ages cover extensive periods of time and are therefore very likely to lack important early life determinants. Likewise, few data sets provide detailed information on genetic endowment or on inherent frailty of individuals. It is well known that ignoring factors that should be included in analyses largely contaminates the estimation of the remaining parameters. Our paper presents an approach to thoroughly assess the role of early life and contemporaneous macro conditions in explaining health trends later in life, controlling for a large range of individual determinants. This requires an appropriate and rigorous treatment of the unobserved part, if we want to eliminate the biases that omitted variables can generate. We present our estimation strategy in much detail in section 2.

We apply our method on Dutch trends in self-reports on functional status at older ages (for a complete review on trends in functional status and disability status at older ages, see Portrait, Deeg, and Alessie 2003). Functional limitations are restrictions in performing fundamental physical actions used in daily life. Functional status is an important aspect of the health-related quality of life of older individuals and most strongly associated with the use of health care services. Recently, an increasing trend in functional limitations at older ages has been shown in the Netherlands (e.g. Hoeymans et al. 1997, Perenboom 2002). Our analyse helps the understanding of the current increasing trends and provides some insights in whether these trends will continue in the future. Especially in the context of an aging population, increasing trends in functional limitations may put extra pressure on the already congested Dutch health care markets.

Our analyses are performed using data from the Longitudinal Aging Study Amsterdam, an ongoing study which follows a representative sample of Dutch individuals aged 55-85 at the onset of the study in 1992. The data set contains detailed individual health information. Statistics Netherlands provides information on the macro determinants. To identify the possible determinants of health at older ages, we use epidemiologic and economic theory as well as empirical evidence. Of course, the actual choice of the variables in the empirical analyses is determined by data availability and some information will be missing. We justify the choice of our health determinants in section 3.

The major advantage of panel data is that we can take into account unobserved heterogeneity. However, panel data, specifically on older populations, may suffer from selective attrition due to mortality or refusals. The paper thoroughly corrects for the effects of selective attrition. The strategy that we follow is presented in much detail in section 2.2. Finally, we include a variety of statistical checks to assess the validity of our results; particularly we tested whether the effects of the early life and contemporaneous conditions are correctly modeled.

Our study touches upon the literature that tackles the basic identification problem of the age, period, and cohort (APC) effects. The contemporaneous conditions, like the access or quality of health care, are referred to as period effects. These factors affect the health status of all cohorts at the time of occurrence. The macro conditions that different birth-cohorts have experienced at birth or during their life refers to cohort effects. In the APC literature, age effects are characterized by age, period effects by the calendar year during which the period effects took place, and cohort effects by the year of birth of the relevant cohorts. The use of dummies is a very flexible way of characterization of the APC effects, and will be occasionally applied in our estimation strategy. However, research that aims at assessing the role of APC factors in explaining trends faces a serious identification problem. Indeed, APC effects are perfectly linearly related as year of birth plus age equals calendar year. The usual way out to handle the perfect collinearity is to restrict in some ways the parameters of the model (see for instance Mason and Fienberg 1985; Reynolds 1998; Alwin & McCammon 2001). Therefore the coefficients are identified on the basis of statistical grounds or of some required assumptions that can not be tested (see e.g. Mason and Fienberg 1985). Moreover, dummies are very poor proxies for the unobserved underlying effects (Heckman and Robb 1985). For instance, the year of birth is a very crude measure of all the environmental macro-influences that a specific cohort faced during lifetime that may affect his or her odds of survival. Additionally, dummies are not informative about the causal mechanisms underlying the effects of macro conditions on mortality. Our approach to model the cohort and time effects explicitly is the approach suggested by Nydegger

(1981) and Heckman and Robb (1985). To our knowledge, this approach is innovative in the literature on health trends and has been seldom applied in other area's (for a recent economic application of the method, see Kapteyn, Alessie, Lusardi 2005). Note further that we explicitly model cohort *and* period effects and that we correct for selective attrition. As far as we know, this has not been done before in the APC literature. The method has two main advantages: to handle the APC identification problem without using statistical assumptions that can not be tested, and to reveal some of the mechanisms underlying health trends at older ages.

The remainder of this paper is organized as follows. The estimation strategy is discussed in much detail in section 2. More specifically, the method and the impact of omitted variables, of unobserved heterogeneity and of selective attrition on the results are dealt with. Section 3 presents the data set and discusses the variables used in the empirical part. Section 4 reports the results of our analyses. Section 5 discusses the results and concludes.

2 Estimation method

2.1 Model

Assume a panel data set that includes I respondents at baseline and T waves. After pooling the data of the T waves together, we can express the health status indicator H as a function of a vector of individual socio-economic and demographic background characteristics x, age a, the current macro conditions PV, and the macro conditions earlier in life CV. K_1 refers to the number of included early life indicators, and K_2 refers to the number of the included contemporaneous indicators. $f(a)$ is a linear spline function of age with K_3 knots. α, β, γ_k, for k running from 1 till K_1, δ_k, for k running from 1 till K_2, and ζ_k, for k running from 1 till K_3 are the parameters to be estimated and v_i^t is the error term. In obvious notation,

$$H_i^t = \alpha + x_i^{t\prime}\beta + \sum_{k=1}^{K_1} CV_{i,k}\gamma_k + \sum_{k=1}^{K_2} PV_k^t\delta_k + \sum_{k=1}^{K_3} f_k(a_i^t)\zeta_k + v_i^t \qquad (1)$$

Identification of the model rests upon the assumption that the macro-indicators of early conditions do not depend linearly on the variable year of birth and the macro indicators for the contemporaneous conditions do not depend linearly on the calendar year.[1]

As already mentioned, some macro information may be missing. Moreover, information on determinants of health such as genetic factors or inherent frailty is generally not available. An appropriate and rigorous treatment of the unobserved part is required if we want to trust the conclusions of the empirical analysis. This is the main focus of the next section.

2.2 Empirical specification

Omitted relevant variables Excluding possibly important macro variables may result in "spurious" associations between health and the included covariates. This is because these macro variables typically exhibit a clear trend and this trend could be related with trends in health. With respect to the early life conditions, we address the "spurious regression" problem by adding a quadratic "year of birth" term (Kapteyn et al. 2005). In a similar way, we include a quadratic "year of interview" to address the possible "spurious correlation" issue between health and the contemporaneous macro variables. We could not include "year of birth" and "calendar year" at the same time because of the linearity constraint with age. If the included macro-indicators still partly explain the health variable after inclusion of the quadratic terms, we can conclude that the macro variables are significantly associated with health.

[1] To maintain identification of model (**??**), K_1 should be smaller than the total number of cohorts minus 2 and K_2 must be smaller than the total number of periods minus 2 (Kapteyn et al. 2005).

After correction for this possible "spurious regression" problem, we check whether we were able to explain most – if not all – of the early life and contemporaneous effects. This can be tested using a Wald test (Kapteyn et al. 2005). For instance, to test the validity of our early life variables, model (**??**) can be tested against a general model including age a, early life and contemporaneous indicators CV and PV, and an arbitrary set of $(C - K_1 - 2)$ cohort dummies (where C is the number of birth cohorts in our analyses). The specification test is on the joint significance of the additional cohort dummies. If the parameters of these cohort dummies are not jointly different from zero, we may claim that model (**??**) is correctly specified and that the cohort effects are appropriately described by the macro-indicators included in the model. We follow a similar approach to test whether we explain most of the contemporaneous effects.

Unobserved individual effects Unobserved components such as genetic endowment or inherent frailty might induce an observed correlation between health and the health determinants. Specification (**??**) should be adjusted for the impact of unobserved heterogeneity, if we want to consistently estimate the included parameters. The error term v_i^t is likely to be correlated with the right-hand-side variables. In order to get more insight into this correlation, we write v_i^t as:

$$v_i^t = c_i + u_i^t$$

where u_i^t is an idiosyncratic error term which might be correlated over time due to unanticipated permanent health shocks[2]. The term c_i reflects time-constant unobserved characteristics such as genetic factors or inherent frailty. The latter factors are determinants of health and may be correlated with demographic and socio-economic characteristics of the individual X_i^t (X_i^t, in

[2]We do not take into account for state dependence in our analyse. Allowing for true state dependence would complicate the analysis a lot especially if one allows for arbitrary autocorrelation structure in u_i^t.

contrast to x_i^t, include the early life and contemporaneous determinants, and the age spline variables): $E(c_i \mid X_i^1, \ldots X_i^T) \neq 0$. The right-hand variables in our health model are assumed to be *strictly exogenous* conditional on the unobserved effect c_i, i.e:

$$E(u_i^t \mid X_i^1, \ldots X_i^T, c_i) = 0$$

which entails that the explanatory variables in each time period are uncorrelated with the idiosyncratic error term u_i^t.

We opt for a Mundlak approach (1978) to deal with the correlation between c_i and the right-hand side variables by including in model (**??**) and models based on (**??**) individual specific averages for the time-varying variables. In our context, the Mundlak's approach boils down to the estimation of:

$$H_i^t = \alpha + x_i^{t\prime}\beta + \sum_{k=1}^{K_1} CV_{i,k}\gamma_k + \sum_{k=1}^{K_2} PV_k^t\delta_k + \sum_{k=1}^{K_3} f_k(a_i^t)\zeta_k + \overline{x_i}'\pi + \omega_i + u_i^t \tag{2}$$

where $\overline{x_i}$ refers to the individual specific averages for the time-varying variables and π refers to the associated parameters. It is important to note that the remaining individual effect ω_i and the included regressors are assumed to be uncorrelated.

Attrition Panel data, especially on older populations, may suffer from selective attrition through mortality and refusals. As a result, an initially random sample may end up as a selective sample where the relatively healthy individuals are over- or under-represented. This leads to inconsistent parameter estimates of the explanatory variables.

Our technique for testing and correcting for attrition bias follows the approach of Wooldridge (2002, chapter 17, sections 17.7.2 and 17.7.3) in a linear panel data model with unobserved heterogeneity. As a simple test for selective attrition, Wooldridge (2002, p. 581)[3] suggests to include, e.g. in model (**??**), a selection indicator, say s_i^{t+1}, equal to one if respondent i participates to the study at $(t+1)$ and to zero if not. Under the null hypothesis – i.e. absence of selective attrition –, the coefficient of the selection variable s_i^{t+1} should not be significant.

Correcting for attrition bias is more complicated. We extend the method presented by Wooldridge (2002) in section 17.7.3 for a fixed effects approach to a random effects approach. First, note that the method presented here treats attrition as an absorbing state, implying that respondents who leave the sample at t do not re-enter the sample at $\tau > t$[4]. Shortly, the Wooldridge approach requires two equations which model the attrition between wave 1 and 2, and between wave 2 and 3 respectively[5]. From those selection equations, summary measures (namely inverse mill's ratio's) can be constructed that summarize the information on attrition available in the selection equations. Finally we estimate the health equations in which the summary measures are included (in order to correct for endogeneous selection).

More formally, consider the following panel data model (using the same notation as before):

$$H_i^t = X_i^{t}{}'\theta + c_i + u_i^t \tag{3}$$

where θ refers to the parameters associated with X_i^t. Conditional on $s_i^{t-1} = 1$, write a (reduced form) selection equation for $t \geq 2$ as:

$$s_i^t = 1\left[z_i^{t}{}'\eta_t + \mu_i^t\right],\ \mu_i^t \mid \left\{z_i^t, s_i^{t-1} = 1\right\} \sim \text{Normal}(0,1) \tag{4}$$

where 1 is an indicator function. z_i^t must contain variables observed at time t for all individuals with $s_i^{t-1} = 1$. z_i^t may, for instance, include the variables in X_i^{t-1}. η_t refers to the parameters associated with z_i^t and μ_i^t is the error term

[3]Verbeek and Nijman (1992) present a similar approach.

[4]In our empirical study, attrition is indeed an absorbing state.

[5]In our empirical study, we have three waves. Obviously with more waves, we need more selection equations

of the selection equation. We will also include some exclusion restrictions (see section **??**).

In order to estimate the model, we make the following two assumptions. First,

$$\mathrm{E}(c_i \mid \overline{X}_i, \mu_i^t) = \overline{X}_i' \pi + \xi_t \mu_i^t \tag{5}$$

where $\overline{X_i}$ are the sample individual averages of X_i^t, π and ξ_t a set of parameters to be estimated. This assumption is basically an adapted version of the "Mundlak" approach (cf. assumption 17.7c of Wooldridge, 2002, page 583). Second,

$$\mathrm{E}(u_i^t \mid c_i, X_i, z_i^t, \mu_i^t, s_i^{t-1}) = \mathrm{E}(u_i^t \mid \mu_i^t) = \rho_t \mu_i^t \tag{6}$$

where ρ_t is a parameter to be estimated (cf. equation 17.60 of Wooldridge, 2002, page 586). Equations (**??**), (**??**), (**??**) imply that:

$$\mathrm{E}(H_i^t \mid X_i, \mu_i^t) = X_i^t \theta + \overline{X}_i' \pi + \phi_t \mu_i^t \tag{7}$$

where $\phi_t = \xi_t + \rho_t$. If we condition on $s_i^t = 1$ instead of on μ_i^t (because $s_i^{t-1} = 1$ when $s_i^t = 1$, we do not have to condition on $s_i^{t-1} = 1$), we get:

$$\begin{aligned}
\mathrm{E}(H_i^1 \mid X_i) &= X_i^{1}\text{'}\theta + \overline{X}_i\text{'}\pi = W_i^{1}\text{'}\Theta \qquad (8)\\
\mathrm{E}(H_i^2 \mid X_i, s_i^2 = 1) &= X_i^2 mbox'\theta + \overline{X}_i\text{'}\pi + \phi_2 \lambda(z_i^{2}\text{'}\eta_2) = W_i^{2}\text{'}\Theta \\
\mathrm{E}(H_i^3 \mid X_i, s_i^3 = 1) &= X_i^{3}\text{'}\theta + \overline{X}_i\text{'}\pi + \phi_3 \lambda(z_i^{3}\text{'}\eta_3) = W_i^{3}\text{'}\Theta \\
&\vdots \\
\mathrm{E}(H_i^T \mid X_i, s_i^T = 1) &= X_i^{T}\text{'}\theta + \overline{X}_i\text{'}\pi + \phi_T \lambda(z_i^{T}\text{'}\eta_T) = W_i^{T}\text{'}\Theta
\end{aligned}$$

where $\lambda(z_i^{2}\text{'}\eta_2)$, $\lambda(z_i^{3}\text{'}\eta_3)$, and $\lambda(z_i^{T}\text{'}\eta_T)$ are the inverse Mills ratio's associated with the sample selection equations (**??**) for $t = 2, 3$ and T,
$\Theta = (\theta', \pi', \phi_2, \phi_3, \cdots, \phi_T)'$, $W_i^{1}\text{'} = (X_i^{1}\text{'}, \bar{X}_i\text{'}, 0, 0, \cdots, 0)'$,
$W_i^{2}\text{'} = (X_i^{2}\text{'}, \bar{X}_i\text{'}, \lambda(z_i^{2}\text{'}\eta_2), 0, \cdots, 0)'$, $W_i^{3}\text{'} = (X_i^{3}\text{'}, \bar{X}_i\text{'}, 0, \lambda(z_i^{3}\text{'}\eta_3))', \cdots, 0)'$, and $W_i^{T}\text{'} = (X_i^{T}\text{'}, \bar{X}_i\text{'}, 0, 0, \cdots, \lambda(z_i^{T}\text{'}\eta_T))'$. It now follows that pooled OLS of H_i^t on X_i^t, $\overline{X_i}$, $d2_i\widehat{\lambda}_i^2$, $d3_i\widehat{\lambda}_i^3$, $\cdots$, $dT_i\widehat{\lambda}_i^T$ – where $d2_i$, $d3_i$, and dT_i are wave

(time) dummies and $\widehat{\lambda}_i^2$, $\widehat{\lambda}_i^3$, and $\widehat{\lambda}_i^T$ are the inverse Mill ratio's computed after estimation of the selection equations (**??**) associated with $t = 2, 3$, and T – yield consistent estimates for Θ (see Wooldridge 2002 for further details). The selection equations (**??**) are estimated using a probit specification.

Final empirical specification The final empirical estimation is given by (for equation (**??**) and using the same notation as before):

$$
\begin{aligned}
H_i^t \;\; = \;\; & \alpha + x_i^t\beta + \sum_{k=1}^{K_1} CV_{i,k}\gamma_k + \sum_{k=1}^{K_2} PV_k^t\delta_k + \sum_{k=1}^{K_3} f(a_i^t)\zeta_k + \overline{x_i}\pi + \phi_2 d2_i\widehat{\lambda}_i^2 \\
& + \phi_3 d3_i\widehat{\lambda}_i^3 + \cdots + \phi_T dT_i\widehat{\lambda}_i^T + \omega_i + u_i^t
\end{aligned} \tag{9}
$$

Since we use a two-step estimation procedure, we have to correct the standard errors resulting from our analyses. We do that using the formulae of Wooldridge (2002, section 12.5) (A detailed exposition of the computation of the standard errors is available on request by the authors). The obtained standard errors are robust to the presence of heteroscedasticity and autocorrelation. STATA is used to perform the calculations.

To conclude this section, it can be mentioned that, if we succeed in correcting for the effects of spurious correlation, of unobserved heterogeneity and of selective attrition, the included variables on early life and contemporaneous conditions have a causal effect on health.

3 Data and Measures

3.1 Data

The analyses in the current study are conducted using data from the Longitudinal Aging Study Amsterdam (LASA), an ongoing multidisciplinary research project. The design and purposes of the LASA study are described in detail elsewhere (Deeg and Westendorp de Serière 1994, Deeg et al. 1998).

The LASA study follows a sample of 3,107 individuals aged 55-85 at the first measurement point. For the study at hand, we use the first three waves, conducted in 1992-1993, in 1995-1996, and in 1998-1999. The data are representative of the Dutch older population. Within each wave, one can distinguish two periods (one for each calendar year). Table 1 below summarizes the attrition in LASA.

< Insert Table 1 about here. >

First, respondents with a telephone interview are excluded from the study as no sufficient information is available on them to address the research question. Second, loss to follow up is to a large extent caused by morbidity or mortality (about 85%, after exclusion of the telephone interviews). As a result of sample selection, we suspect that healthier individuals have a higher probability to remain in the sample (Deeg et al. 2002). In other words, the sample attrition is presumably endogeneous. Third, given the low number of refusals, we do not model separately the loss to follow up due to refusals.

3.2 Measures:

Health status We illustrate our estimation strategy by applying it on trends in self-reports on functional status of older individuals (FL). Functional limitations are measured in the LASA study by self-reports on mobility activities in daily life. These self-reports include the ability of respondents to: (1) cut one's own toenails, (2) walk up and down a 15-steps staircase without stopping, and (3) make use of private or public transportation (Mc Whinnie 1981, van Sonsbeek 1988). Note that the choice of these three items has been done step-wise: in the LASA pilot study, nine items were used to measure functional ability and the selected three items were the most consistent ones to describe functional ability (Kriegsman 1997; Smits 1997). The score takes on value 0, 1, 2 when a test item is performed without any difficulty, with difficulties or only with help respectively. A score equal to 3 is given to the respondent when the activity can not be performed. The total score is obtained by summing the three activity scores. The internal consistency of the three items is very good (Cronbach's alpha: 0.76); the test-retest reliability excellent (weighted kappa's between 0.76 and 0.90) (Boshuizen, Chorus, and Deeg 2000). Table 2 reports descriptive statistics on functional limitations at wave I.

< Insert Table 2 about here. >

Macro determinants In his theoretical framework for health and survival, Schultz (1984) distinguishes five categories of macro determinants that may affect health instantaneously but also later in life: 1) Market prices and wage rates to account for the general economic situation, 2) Public (health care) programs, 3) Climate and Disease exposure 4) Availability of information on, for instance, hazardous or health-enhancing activities and 5) Infrastructure like the availability of drinking water or sewage. Briefly, there seems to have grown a consensus on the fact that especially bad nutrition and exposure to diseases during pregnancy, infancy and childhood (see Fridlizius 1989, Fogel 1994, Barker 1998) hinder the normal development of the body and cause permanent damages that affect health instantaneously and at later ages. This forms the framework to select our macro variables[6].

Instead of using food prices or wage rates (not available for all birth-cohorts), we proxy the general economic conditions by the real Gross National Product (G.N.P.) per capita during pregnancy, at age 1, at ages 1-5 , at ages 5-15 (periods of growth of the children), and at ages 15-22 (at the entrance on the job market) (see van den Berg, Lindeboom, and Portrait 2006 for a review of the effect of macro-economic conditions on mortality). Our analyses also account for the famine of unprecedented severity that the cities in the West of the Netherlands experienced in the winter of 1944/45; we investigate whether

[6]Our macro-data are from Statistics Netherlands.

experiencing malnutrition during childhood (at ages 12, 16 and 18)[7] affect functional status at older ages.

With respect to public programs, the Netherlands faced severe restrictions in availability in acute and long-term care facilities during the observation window (see, e.g., Portrait 2000). We include: 1) the number of hospital beds per 1,000 inhabitants aged 65 and above, 2) the number of nursing days in hospitals per 1,000 inhabitants aged 65 and above, 3) the average duration of stays in hospitals, 4) the number of persons in residential homes per 1,000 individuals aged 65 and above, 5) the number of nursing days in nursing homes per 1,000 inhabitants aged 65 and above, 6) the number of workers in home care organizations per 1,000 individuals aged 65 and above, and 7) the proportion of middle-aged females participating in the labor market as they are an important source of informal care of disabled older individuals. Finally, the Netherlands went through a rapid increase in work-related disability from the seventies till 1990. This may have affected the reporting behavior for two main reasons. First, it became more and more accepted to be disabled. Second, individuals possibly overstated their disability status to have access to the generous disability schemes. To address this, we investigate whether the proportion of individuals participating in disability schemes when the respondent was aged 30-40, 40-50 and 50-60 affect the trends in functional limitations.

Regarding climate exposure, cohorts that grew up during cold winters and rainy springs may have had worse living conditions and less access to (good quality) food (see for instance Doblhammer and Vaupel 2000). To address this, we include as cohort variables average temperature in the winter at birth and at ages 1-5[8]. Regarding exposure to diseases, we include: the percentage of deceased individuals due to infectious diseases, due to tuberculosis, and due to cancer at birth of the respondent, and between age 1 and 5. We also

[7] We can not study the effect of experiencing a famine at ages under 12 since the youngest LASA respondents are born in 1937.

[8] Information on springs is not available for all cohorts.

include infant mortality under age 1. Influenza caused a dramatic epidemic in 1918. We included dummy variables indicating whether the respondent was under age 5 and under age 14 in 1918.

Information availability is proxied by a variable indicating the average attained level of education of fathers at birth of the respondent and the average level of attained education level of children when the respondent was 14 years of age. Finally, regarding infrastructure, we could not find any good data on the availability of sewage and drinking water facilities for the LASA respondents. However, the major investments in public health were made from 1870th till the end of the 19th century. Therefore we can assume that all LASA respondents grew up in favorable conditions with respect to sewers and water supply.

In addition to the five categories of the Schultz framework, we should mention that our sample is conditional on survival up to the beginning of the observation window. A substantial part of the cohort effects may be muted since we only observe the fittest members of each cohort. Due to the design of the data, our conclusions with respect to cohort effects only concern individuals that survive till at least age 55. We attempted to correct our analyses for this survivorship bias by including variables indicating differences in prior death in successive cohorts. The four variables indicate the number of survivors to ages 1, 15, 40, and 50 out of 100.000 individuals per year of birth and sex (Tabeau et al. 1994).

Table 3 provides information on most cohort variables and shows that the trends are as expected: decreasing infant mortality, a steady decline of the number of deaths due to infectious diseases and/or tuberculosis and of the infant mortality with the exception of the years around the first World War, a slight increase of the average education level of the father and of the children, an increasing G.N.P. till 1921 slightly decreasing afterwards, and an increasing percentage of individuals with disability schemes after 1970. Table 4 provides information on the period variables. It shows a decreasing availability of care services (except for the use of nursing homes) and an increasing female labor participation during the observation window.

< Insert Tables 3, and 4 about here. >

Independent variables Additional demographic and socio-economic covariates are: female (0 = "male", 1 = "female"), attained education level of the respondent (three dummies ranging from "elementary education not completed" till "university education"), household real net monthly income in 1,000 euro, occupational prestige of the longest job according to Sixma and Ultee (1983) (ranging from 0 = "never had job" till 87 = "high prestige"), place of residence (two dummies for "North-East", and "South", with reference category "West"), and partner status (0 ="no partner", 1 = "partner"), and whether the respondent experienced a significant event (war, poverty etc) during childhood (0 = "no", 1 = "yes")[9]. In the empirical part, we also include interaction variables between age and gender, as health trends at older ages may depend on gender[10]. Table 2 reports descriptive statistics on the demographic and socioeconomic variables at wave I.

Dummies for Age, Year of birth and Calendar time Using full sets of dummies for the years of birth, for calendar time and for age is a very flexible way of modeling the effects of early life and contemporaneous conditions and of age. We occasionally follow this strategy in the empirical part. For the problem at hand, this boils down to using 30 dummies for year of birth (respondents are born in years 1907-1936), 37 dummies for age (respondents are aged 55-91 during the observation window), and 6 dummies for the timing

[9]We also include a variable indicating missing values for this variable (4.4% missing at wave I).

[10]We also estimated models including interaction variables between gender and the age splines function. We can not reject the assumption that the coefficients of the interaction variables are the same. Therefore, we decided to work with a single interaction variable between gender and age.

of interview (interviews are hold in 1992, 1993, 1995, 1996, 1998, and 1999). To save some degrees of freedom, a spline approach is also followed to model age and year of birth. Age effects are characterized using piecewise linear splines (with 4 knots spaced over the range of age, namely 62.9, 69.4, 76.6, and 83.8 years of age).[11].

Exclusion restrictions As we said before, our model includes two selection equations. The first (second) equation explains the attrition between wave 1 (2) and 2 (3). In those selection equations, we included the same age, cohort, and same background characteristics as in the health equations. Moreover, we add a time dummy which indicates whether the respondent participates in the second period within a wave.

Finally, we have to come up with variables that explain attrition due to mortality, being too ill, and refusals and that do not explain functional limitations outcomes, for instance variables indicating too little spare time to participate in the study. Those exclusion restrictions are crucial if we want to thoroughly correct for attrition. We are in the fortunate position to have access to two convincing exclusion restrictions variables: a dummy indicating whether a female is a member of a non-Roman catholic church, and a categorical variable indicating whether the participation to LASA was enjoyable or not, ranging from 1 = "very unpleasant" till 5 = "very pleasant".[12] With respect to the latter, it is worth mentioning that the question is divided in two parts: a first part assessing whether the participation was tiring or not (which may be highly related to health status), and a second part assessing whether the respondent enjoyed the participation. The second part is much less likely to be associated with health status, and is consequently used in our analyses. In the empirical part, we converted the latter variable in five dummies (enjoy1 till enjoy5). Moreover, we constructed additional exclusion

[11]In preliminary analyses, we extended the number of knots. However, the results remain to a large extent similar.

[12]In case of male respondent, membership of a church did not explain attrition.

variables by interacting the dummy variables “enjoy” with the binary variable ”female”, and with the dummy variable which indicates whether the respondent participates in the second period within a wave. We only retain in the final specification of the selection equations the significant interaction terms, namely female*enjoy2, female*enjoy3 and the dummy for the second period in the wave *enjoy3.[13]. We also experimented with additional variables such as categorical variables indicating the number of children, the number of grand-children, whether the respondent has currently a pay job, and the degree of participation in social organizations. These variables do not predict attrition. We also experimented with interaction variables with age and gender. In total, we have 8 exclusion restrictions.

< Insert Tables 2, 3, and 4 about here. >

4 Results

Table 5 reports the results of specification (a) including age splines, period dummies and cohort variables, specification (b) including age splines, cohort and period variables, and specification (c) including age splines, cohort and period variables as well as demographic and socio-economic characteristics[14].

< Insert Table 5 about here >

4.1 Health equations

Attrition First of all, to decide whether we should correct for selective attrition, we have performed the test on selective attrition suggested by

[13]The results are not affected by leaving out the non significant exclusion terms. However, the estimates become more precise.

[14]We do not show the full estimation results of the selection equations as we are not interested in the parameters estimates (results available on request by the authors).

Wooldridge (2002, p.581) in all specifications (full results available on request by the authors). The selection dummy s_i^{t+1} was negative and very statistically significant, showing that respondents who remain in the LASA study report on average less functional limitations than the attriters. This indicates that, to get correct parameter estimates, one needs to control for selective attrition. We do that using the techniques derived in section 2.2 to correct for selective attrition in the context of a random effects linear model with unobserved heterogeneity[15].

First, the exclusion variables are strong predictors of the participation to LASA in successive waves, namely the female members of a non Roman catholic church and the individuals who enjoyed the participation in the first wave were more likely to participate in successive waves than others. The χ^2- tests (8 degrees of freedom) are reported in table 5 and show that the exclusion restrictions are jointly significant in the selection equations. We admit however that the χ^2-values are not that high, indicating that the exclusion restrictions are not really powerful.

Second, the parameters associated with the inverse Mill ratio's are all negative and significant in specifications (a) and (b) at the 10% level. This indicates that the unobservables determining attrition after we correct for observed characteristics are negatively correlated with those determining individual health status.

Age, Cohort and Period variables A significant increasing age effect is found in all specifications (p-value equal to 0 in all specifications, see table 5): the older the individuals are, the more functional limitations they report (after approximately age 69 in all specifications). The spline parameters are

[15] We have also estimated the attrition bias fixed effects model of Wooldridge (2002). In this model, the cohort effects are subsumed in the individual effects and the time effects are modeled by means of macro-indicators. In this way, we were able to check whether our approach and that of Wooldridge yielded similar estimates for the age coefficients. From our sensitivity analysis, this appeared to be the case (results are available upon request).

to a large extent similar in specifications (a) and (b), and slightly lower in specification (c).

In preliminary analyses, we estimated specification (a) including step-wise all cohort variables described in section 3.2. We could not find any strong evidence of cohort effects. The variable that had the highest explanatory power (t-value equal to 0.92) was the variable indicating the number of deaths due to tuberculosis in the first year of the respondent. All other cohort variables had no or a lower explanatory power. To check whether the "tuberculosis" cohort variable should nevertheless be included in our model, we re-estimated specification (c) without including the cohort variable and assessed whether the age and period parameters changed. The age parameters remained very similar: only the slope at younger ages (age 69-77) was a little bit steeper in the specification excluding the "tuberculosis" variable. However, the size of the period effects decreased slightly. Therefore, we decided to keep the "tuberculosis" variable in the final specifications.

Furthermore, note that we included in previous work the "year of birth squared" to correct for possible spurious regression problems (see section 2.2). However, the variable indicating "year of birth squared" was not statistically significant (t-values around 0.12) and the remaining parameters were hardly affected. Consequently, this variable was excluded from the final specifications.

With respect to period effects, a significant increasing trend is shown in specification (a) (p-value equal to 0.0345, see table 5): individuals report more functional limitations at the end of the nineteen-nineties, after correction for age and cohort effects. When including the period variables, we found that the increased prevalence of self-reported functional limitations is related to the restrictions in hospital and home care services (proxied by the number of nursing days in hospital per capita and the number of home care workers per individual aged 65 and above). We could not find any significant effects on functional status of the supply reductions in informal care and in institutional care. We included the variable "calendar year squared" to correct for possible spurious regression problems. The parameter estimate appeared to be negative and statistically significant in all specifications, indicating a decrease in self-reported functional limitations after correction for the impact of restrictions in hospital care and home care.

It is interesting to see that the age, cohort, and gender parameters are to a large extent similar in specifications (a) and (b), which indicates again that the period effects are most likely correctly modeled. After correction for individual characteristics, the parameters associated with the period variables are still jointly significant (see Table 5) (at a 10% level). Specification (c) in which the two period variables were replaced by five period dummies was estimated again to get insight into the direction of the period effects after correction for demographic and socio-economic characteristics. The parameters of the period dummies still showed a significant increasing trend.

Demographic and Socio-economic characteristics In order to take into account possible difference in health trends at older ages between males and females, we decided to include in our final estimations interaction variables between age and gender. We also estimated models including interaction variables between gender and the age splines function. As we could not reject the assumption that the coefficients of the interaction variables were the same, we decided to work with a single interaction variable between gender and age. The results show that females report more functional limitations than males from age 60 onwards and that the prevalence of functional limitations for females increased with age at a significantly higher rate than for males.

With respect to the socio-economic characteristics, the analyses demonstrate that medium educated respondents report significantly less functional limitations than lower educated respondents. Before commenting on the "income" variables, it is worth mentioning that we exclude from the analyses the “Mundlak” variables[16] when they were not statistically significant. In this case, they do not account for a significant correlation between independent variables and error term and they may obscure the interpretation of the covariates because of a high correlation between the covariates and the individual specific averages. Nevertheless, we end up with one significant “Mundlak” variable (namely average income), which shows the need to correct for possible correlation between the unobserved individual effects and the time-varying right-hand side variables. The parameter estimates show that individuals with higher incomes report less functional disorders.

Furthermore, respondents for whom the longest job was a job with a high prestige are less functionally disabled at older ages than others. We find some effect of the region (respondents in North-East report more functional limitations than in West). Strong negative effects on functional status of having experienced a significant event during childhood emerge. Finally, we find a strong positive effect of partner status: having a partner decreases the probability of suffering from functional disorders.

4.2 Sensitivity analyses

First, it is important to test whether the cohort effects are correctly specified. To do so, we re-estimated specifications (b) and (c) in which a full set of cohort dummies (28) were included. We do not reject the hypothesis of correct specification of the cohort effects (p-values above 0.64, see table 5). Similarly, to check whether we explained most of the period effects, we re-estimated specifications (b) and (c) after inclusion of two additional time dummies. The parameters were not jointly significant (see Table 5); therefore it could be concluded that all period effects are explained. However, these results may be driven by the high degree of multicollinearity between the variables. This may result in the fact that we too easily accept the hypothesis

[16] See section 2.2 on the effect of unobserved heterogeneity. Two time-varying regressors are included in our analyses, namely real net monthly income and partner status.

of correct specification of the cohort and period effects. We return to this later on.

Second, we need to check whether our results are not driven by multicollinearity problems between the right hand side variables. To do this, we report the highest variance inflation factors (VIF) and the average VIF in table 5. The VIF of a particular right handside variable j-th, say female, is equal to $1/(1 - R_j^2)$, where R_j^2 denotes the R^2 obtained from regressing the variable j-th on the other explanatory variables. A high VIF could indicate multicollinearity problems. Chatterjee, Hadi and Price (2000) have formulated some rule of thumb for the VIF. According to these rules, there is evidence of multicollinearity: 1) The largest VIF is greater than 10, 2) The mean of all the VIF's is considerably larger than 1.

The largest VIF in specification (a) is equal to 78.35 and corresponds to the variable "female*age". It appears that the variables "female" and "female*age" are strongly correlated with each other: those variables have very high VIF. Note however that the variables "female", "female*age" (and the age spline) are strongly significant. In other words, we do not have to worry about the high VIF of those variables. If we disregard the variables "female" and "female*age", then the variable indicating "tuberculosis" has the highest VIF, equal to 8.25. This value is not particularly high (see the rules of thumb presented above).

In specifications (b) and (c), we replace the time dummies by two period variables and the calendar year squared. Since the variable indicating the number of nursing days in hospitals exhibits a negative trend (see table 4), the VIF of this variable and the calendar year squared variable are very high. The VIF of the other right hand side variables (except for "female" and "female*age") are below 10. Again, the other age, cohort and period variables are not strongly correlated with each other. But we admit that the high VIF of the calendar year squared variable and the hospital nursing days variable indicate strong multicollinearity problems which might result in large standard errors of the estimates. However, those two variables are (almost) statistically significant at a 5% level. From those findings, we can conclude that the problem of multicollinearity between the right hand side is not that severe.

As mentioned previously, we investigated whether the cohort and period effects are correctly specified by testing whether additional cohort and period dummies are still significant in addition to the cohort and period variables. Due to the addition of these variables, the VIF become indeed very high. From this finding we have to conclude that our misspecification test are not that powerful.

Third, as mentioned in section 3.2, our sample may suffer from survivorship bias. To control for this, we added in previous specifications a set of variables indicating differences in prior death in successive cohorts (see section 3.2 for a description of these variables). All parameter estimates associated with the mortality variables were not statistically significant and the remaining parameter estimates were only very slightly affected by the inclusion of these variables. Therefore, we excluded these variables from the final specifications.

Finally, we tested for non-separability of the age, period and cohort effects following an approach developed by maCurdy and Mroz (1995), Gosling et al. (1999), and Fitzenberger et al. (2001). For this test, we consider specification (a) of table 5. Basically, we add a full set of interaction terms between the age spline variables and the time dummies (cf. equation 2-13 of Fitzenberger et al 2005). It appears that those interaction terms are not jointly significant at the 10% level (p-value= 0.113). This result should be interpreted with care because this miss-specification test is not very powerful. This is again because of the multicollinearity problems between the interaction terms.

5 Discussion

The absence of significance of the variables on prior mortality per cohort may be surprising. We checked the validity of this result in two ways: first by including a large range of plausible cohort variables, second by re-estimating specification (b) where the cohort variable was replaced by a full set of cohort dummies. This may be partly explained in the light of the recent literature on the long-term health effects of early life conditions. There is indeed statistical evidence showing that the deterioration of the health status shows up at the oldest ages only. The mechanisms are still unknown, but it is hypothesized that bad conditions in early life results in the deficient development of vital organs and immune system, and that this boils down to a higher prevalence of chronic diseases at older ages (more specifically cardiovascular diseases and possibly cancer) and higher mortality rates (see e.g. Crimmins and Finch 2005, Bengtsson and Lindstrom 2003, Barker 1998). Consequently, we most probably observe the largest part of the cohort effects (at least for the youngest cohorts). An additional explanation could be related to the fact that most results in the recent literature are on chronic diseases and mortality. To our knowledge, there is no evidence of cohort effects for physical limitations at older ages.

Regarding the adverse period effects, a few explanations may be put forward. Individuals may experience (higher level of) functional limitations for a longer period of time as the waiting period for e.g. surgeries or home care increased during the nineteen-nineties. Patients may also be discharged from hospitals earlier which may result in a deterioration of their functional status. When at home, the hospital care can not be fully compensated by home care services, which may lead to a further decline in functional status. Our final specification includes the variable "calendar year squared". The parameter estimate of this variable is negative and significant. This shows a decrease in functional limitations after we rule out impact of the restrictions in acute and home care. In other words, if there had not been cuts in health care facilities, the prevalence in functional limitations would have decreased in the nineteen-nineties. This paper does not explain whether the remaining decreasing trends shows up as a result of, for instance, new technologies or improvement in the quality of the delivered care. This is a topic for future research.

One major limitation of our study is that our data covers a relatively short period of time. At the time of the study, there were only three waves available, and that surely restricts the validity of our results. Interpretation of age effects should therefore be limited to the observed age span, if we want to avoid out-of-sample predictions. In future studies, we surely will enlarge the observation window, as the fourth wave of LASA will become soon available. We nevertheless would like to remind that the purpose of the study is to propose an approach to thoroughly assess the effect of early life conditions and contemporaneous conditions on health later in life, and that we applied our approach to study the trends in functional limitations at older ages as a matter of illustration and also because this is highly related to the use of care.

A second limitation of the study is that, strictly speaking, an ordered probability model should be used in order to take into account that our dependent variable is not measured on a metric scale. However, extending an ordered probit model by taking into account (correlated) unobserved heterogeneity and endogenous attrition, is a very complex exercise. Therefore, we decided to refrain from using this. For similar reasons, we do not take into account for state dependence in our analyses. Indeed, allowing for true state dependence would complicate the analysis a lot especially if one allows for arbitrary autocorrelation structure in uit.

A third limitation of the study is that functional status is self-reported. The observed period effects could be explained by variations in the norms for subjective evaluations over time. Unfortunately, we can not exclude this possibility.

6 Conclusions

The paper presents an approach to thoroughly assess the role of early life and contemporaneous macro conditions in explaining health trends later in life. In particular, we investigate the role of exposure to infectious diseases and economic conditions during infancy and childhood, as well as the effect of current health care facilities. Specific attention is paid to the impact of omitted relevant variables, unobserved heterogeneity and to selective attrition. We apply our approach to recent Dutch trends in functional limitations at older ages. Our analyses are performed using data from the Longitudinal Aging Study Amsterdam. The general conclusion of the modeling approach is that the prevalence of functional limitations at older ages increased for males and females during the nineteen-nineties in the Netherlands and that this is partly explained by adverse period effects – that persist after we correct for demographic and socio-economic variables. Our analyses show that the adverse period effects are due to restrictions in acute and home care services. To conclude, the modeling approach is highly appropriate to understand the mechanisms underlying the trends in health status at older ages.

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Table 1: Pattern of attrition in the LASA study

	Wave I	Wave II	Wave III
Number of participants	3,107	2,302	1,874
Deceased	-	417	344
Too frail	-	55	61
Refusal	-	90	64
Telephone interview	-	243	202

Table 2: Descriptive statistics: Health, Demographic and Socioeconomic factors; Wave I

Variables	Response	(%)
Number of respondents*	2,991	
Self reports on Functional Limitations	0	58.6
	1-3	25.0
	4-6	9.2
	7-9	7.2
Age	55-60	16
	60-65	17.5
	65-70	17
	70-75	15.3
	75-80	18
	80-85	16.2
Year of birth	1908-12	18.2
	1913-17	18.5
	1918-22	15.1
	1923-27	15.8
	1928-32	16.7
	1933-37	15.7
Year of interview	1992	33.9
	1993	66.1
Female		51.2
Attained education level	Low	43.9
	Medium	42.2
	High	13.9
Net monthly income (in Euro)	< 625	22.3
	625-852	22.4
	853-1080	16.7
	1081-1477	18.9
	1478-1932	10.4
	> 1933	9.5
Occupational prestige longest job	Mean	27.2
Place of residence	North-East	30.7
	South	23.9
	West	45.4
Partner status	No partner	33.5
Significant event during childhood	No	72.4

*: After exclusion of missing values.

Table 3: Cohort macro-indicators

Year of birth	Survivors at one year of age per 100,000	No. deaths infectious diseases per 100,000	No. deaths tuberculosis per 100,000	Average education fathers*	Average education children*	Real GNP per capita at birth **	Percentage disability schemes at age 40	Sterfte per 1000 levendgeb.
1908	85,845	246.5	164.0	2.61	3.15	8.14	1.17	29.1
1909	87,740	227.5	164.0	2.38	3.12	8.64	1.17	25.1
1910	86,317	221.0	156.9	2.53	3.45	9.32	1.20	25.6
1911	85,081	229.2	157.0	2.27	2.92	10.45	1.21	30.2
1912	89,200	212.2	144.0	2.18	3.21	11.11	1.24	23.2
1913	88,595	202.4	142.0	2.90	2.89	11.56	1.24	23.0
1914	90,549	202.4	140.0	2.61	3.52	12.54	1.25	23.4
1915	89,333	208.4	144.1	2.40	3.34	16.89	1.27	21.8
1916	89,146	235.5	167.0	2.41	3.13	21.13	1.28	21.8
1917	89,238	243.0	182.0	2.64	3.03	21.96	1.28	23.8
1918	88,106	290.9	203.0	2.38	3.35	28.67	1.31	33.8
1919	92,173	258.0	174.0	2.55	3.40	41.72	1.34	33.2
1920	90,699	195.8	146.9	2.34	3.41	51.51	1.41	31.5
1921	91,951	180.3	127.0	2.41	3.31	41.73	1.44	31.1
1922	92,167	160.2	113.7	2.49	3.25	34.00	1.48	29.0
1923	94,203	150.1	104.8	2.67	3.52	31.43	1.54	26.3
1924	93,170	144.1	106.5	2.65	3.62	32.80	1.68	25.7
1925	94,842	139.2	98.7	2.80	3.26	33.37	1.80	23.6
1926	93,206	144.0	96.2	2.51	3.43	32.43	1.93	24.1
1927	95,125	141.8	94.3	2.80	3.43	32.85	1.82	24.8
1928	93,573	125.7	83.8	2.75	3.39	34.43	1.99	23.6
1929	95,280	124.5	85.6	2.74	3.70	33.89	2.17	24.6
1930	94,316	113.1	74.7	2.45	3.90	31.04	2.27	23.4
1931	94,643	103.9	72.7	2.89	3.78	25.76	2.37	23.4
1932	94,896	94.5	64.4	2.64	3.98	20.98	2.50	22.4
1933	95,161	85.1	59.8	2.67	3.65	19.85	2.63	22.4
1934	95,359	81.0	54.5	2.94	3.80	19.12	2.77	22.5
1935	96,539	75.3	52.4	2.77	3.80	18.05	2.98	22.5
1936	95,620	73.6	50.0	3.00	3.88	17.62	3.83	21.5
1937	95,806	66.9	47.9	2.61	4.07	20.28	4.19	20.9

*: calculation based on an education indicator with scores ranging from 1 (primary education not completed) till 9 (university 2nd grade).

**: real G.N.P. measured in 1.000 Euro with 1990 as base year.

Table 4: Period macro-indicators

Indicators	1992	1993	1995	1996	1998	1999
Nb hospital beds per 1,000 inhabitants	4.2	4.1	3.9	3.8	3.7	3.6
Nb nursing days in hospitals per 1,000 inhabitants	1.1017	1.0756	1.0230	1.0032	0.9448	0.8845
Total number of residential home dwellers	127	124	119	117	108	107
Number nursing days in nursing homes per 65+	9.6227	9.6589	9.7545	9.7581	9.7028	9.57
Number of home care workers per 65+	0.02534	0.02501	0.02438	0.02374	0.02399	0.02375
% working middle-aged females	34.76	34.81	41.44	42.31	45.8	47.07

Table 5: Estimation results model (9) on Self-reported Functional Limitations

	Spec (a)	Spec (b)	Spec (e)
Inv. Mill ratio (t=2)	-0.653*	-0.445**	-0.242
	(0.38)	(0.22)	(0.21)
Inv. Mill ratio (t=3)	-0.935*	-0.925*	-0.611
	(0.51)	(0.50)	(0.47)
Age spline [55,63)	-0.00580	-0.00392	-0.00206
	(0.019)	(0.018)	(0.020)
Age spline [63,69)	0.0172	0.0158	0.00803
	(0.020)	(0.020)	(0.020)
Age spline [69,76)	0.0672***	0.0666***	0.0552**
	(0.025)	(0.025)	(0.024)
Age spline [76,84)	0.191***	0.188***	0.168***
	(0.023)	(0.023)	(0.022)
Age spline [84)	0.323***	0.321***	0.311***
	(0.062)	(0.062)	(0.060)
Period dummy 1993	0.205**		
	(0.080)		
Period dummy 1995	0.215		
	(0.15)		
Period dummy 1996	0.407**		
	(0.16)		
Period dummy 1998	0.130		
	(0.18)		
Period dummy 1999	0.435**		
	(0.20)		
Deaths Tuberculosis at birth	0.00247	0.00245	0.00206
	(0.0027)	(0.0027)	(0.0026)
Nursing days in hospitals		-16.43***	-12.61**
		(5.30)	(5.72)
Number workers in home care per 65+		-1.341**	-1.180*
		(0.61)	(0.66)
(Calendar year)^2		-0.0406***	-0.0302*
		(0.014)	(0.015)
Female	-3.981***	-4.000***	-3.946***
	(0.59)	(0.59)	(0.64)
Female * Age	0.0662***	0.0666***	0.0622***
	(0.0088)	(0.0088)	(0.0095)

Standard errors in parentheses
*** p¡0.01, ** p¡0.05, * p¡0.1

Table 5: Estimation results model (9) on Self-reported Functional Limitations (continued)

	Spec (a)	Spec (b)	Spec (e)
Medium Education			-0.271***
			(0.091)
High Education			-0.153
			(0.14)
Partner Status			-0.0912
			(0.094)
Real income (in 1.000 euros)			-0.00385
			(0.068)
$\overline{\text{Real income}}$			-0.654***
			(0.11)
Childhood event			0.352***
			(0.087)
Dummy Childhood event			1.924***
			(0.33)
Prestige			-0.00262
			(0.0019)
North-East			0.151*
			(0.088)
South			0.0288
			(0.098)
Constant	0.473	18.66***	15.06**
	(1.01)	(5.98)	(6.46)
No. obs	6556	6556	6025
R square	0.259	0.259	0.286
Adj. R square	0.257	0.257	0.283
p-value χ^2-test age splines	0	0	0
p-value χ^2-test time variables	0.0345	0.00754	0.0875
Highest variance inflation factor	78.35	214.1	220.1
Average variance inflation factor	17.45	50.10	29.62
χ^2-value exclusion restrictions selection equation 1	46.20	46.20	40.05
χ^2-value exclusion restrictions selection equation 2	35.69	35.69	34.39
p-value misspecification test presence cohort effects		0.648	0.640
p-value misspecification time effects		0.632	0.531

Standard errors in parentheses

*** p¡0.01, ** p¡0.05, * p¡0.1