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PERIOD AND COHORT EFFECTS ON ELDERLY MORTALITY: A NEW RELATIONAL MODEL FOR SMOOTHING MORTALITY SURFACES

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1. INTRODUCTION

It is well acknowledged that mortality surfaces are a powerful tool for demographic research. The impact of age, period, and cohort effects on mortality is easily traced in the graphic representation of mortality rates represented as a function of age and time (Arthur and Vaupel 1984, Caselli, Vaupel and Yashin 1985). At aggregate level, hence, the analysis of mortality surfaces offers the best opportunity to address one of the topics that is increasingly becoming of great interest for demographers: the relative importance of cohort versus period effects on elderly mortality. What are the main factors affecting adult and old mortality? How much continuity is there in an individual's life and how much plasticity? A large body of studies addresses the question about the importance of early-life and current conditions for mortality in later-life. Table 1 synthetically reviews some of these works (for extensive reviews see e.g. Elo and Preston 1992, Doblhammer 2004, Myrskylä 2010a,b). Although incomplete, this list includes studies that account for a quite wide range of hypotheses. The findings of these studies, however, are mixed, and the above questions are still waiting for a conclusive answer.

In this paper we consider two main questions: To what extent do early-life and current factors determine trends in old-age mortality? Did early life factors determine the decline of adult and old mortality in the second half of the 20^{th} century in the European countries? We present a new explanatory but flexible relational model to analyse mortality surfaces including period and cohort indicators. This two-dimensional model is estimated via a semi-parametric approach by smoothing the general mortality trend over age and time with penalized *B*-splines. This allows, on one hand, to keep the non-linear structure of mortality dynamics over the long term, and on the other hand to evaluate simultaneously the relative importance of period and cohort effects. We apply the described model to two case studies, Sweden and Italy, which have been chosen because of their different past mortality dynamics.

TABLE 1[1]

The debate on the importance of cohort and period factors on longevity

Kermack et al. 1934, 2001	Child mortality determines mortality at older ages. Debilitation events are primarily important during the first 15 years of life.
Livi-Bacci, 1962	Positive correlation between mortality levels in infancy and in old ages for cohorts born between 1871 and 1891 in sixteen Italian regions. Many important events may occur from birth to old age and hence a possible selection effect due to high infant mortality should only have a slight impact on mortality at old ages.
Forsdahl, 1977	Children who experience the worst living conditions during childhood were the most at risk of heart disease later in adulthood
Horiuchi, 1983	Elevated mortality at old age for cohorts involved in the World War I at younger ages.
Caselli and Capocaccia, 1989	Negative effects due to unfavourable living conditions during the early period of life continue during adulthood and entail greater vulnerability in the survivors up to age 45. At older ages selection is active.
Fogel, 1993	Association between individuals' height - a measure of nutrition and health during infancy and early childhood - and chronic diseases later in life.
Barker, 1994, 1995	Preconditions for later diseases (coronary hearth diseases) are initiated in utero due to poor nutrition of the mother during pregnancy.
Kannisto et al., 1997	Survival in childhood and adolescence is lower for cohorts born before and during a famine but mortality at adult and old ages is not affected. Current conditions may be more important.
Davey Smith et al., 1998	Adverse socio-economic environment in early life has influence only on particular diseases in adulthood (e.g. stroke, stomach cancer).
Bengtsson and Lindstrom, 2000	Disease load during the first year of life (rather than nutrition in utero) has a strong impact on late life mortality, particularly on the outcome of airborne infectious diseases during old age.
Davey Smith and Kuh, 2001	In the second half of 20th century, with the change in the cause-of-death profile and medical progress, period factors become more important.
Doblhammer and Vaupel, 2001	Month-of-birth patterns in infant mortality and mortality at ages 50 and over are highly positively correlated. Seasonal factors responsible for infant mortality lead to debilitation of the survivors and to increased mortality later in life.
Barbi and Caselli, 2003	Minor impact of infant mortality on elderly mortality. Frailty acquired during the working age may lead to higher mortality after retirement but, at older ages, this debilitation is counterbalanced by higher selection.
Finch and Crimmins, 2004	Decreased inflammation during early life has led directly to a decrease in morbidity and mortality resulting from chronic conditions in old age.
Barbi and Vaupel, 2005	Various early-life factors have been shown to affect late-life mortality. However, demographic and epidemiological studies suggest that the effect is modest.
Crimmins and Finch, 2006	Increasing longevity and declining mortality in the elderly occurred among the same birth cohorts that experienced a reduction in mortality at younger ages. These cohorts also experienced increasing adult height. Both the decline in old-age mortality and the increase in height may been promoted by the reduced burden of infections and inflammation.
Van den Berg et al., 2007	Males exposed to the Dutch potato famine (1846-47) in utero may have increased mortality at ages above 50. For women no effects are found
Van den Berg et al., 2009	No evidence for any links between mortality conditions at birth and adult mortality.
Myrskylä, 2010a	Early life conditions have a transitory effect and potentially only little influence on old-age mortality.

2. DATA

Our analyses focus on adult and old-age mortality (ages 50-99) in the second half of the 20*th* century in two countries with different mortality experiences, Sweden and Italy, for men and women separately. These two countries differ in the way and speed in which they experienced the demographic transition. Like other Northern European countries, Sweden is characterized by an early start of the mortality transition. In contrast, Italy experienced a delay with respect to the Northern European countries, in particular with respect to Sweden, Norway and

[1] An earlier version of this table has appeared in E. Barbi, F. Janssen, J.W. Vaupel "Modelling Mortality Surfaces: Period and Cohort Influences on Elderly Mortality in Italy and Sweden". Paper presented at the 1st Human Mortality Database Symposium. Max Planck Institute for Demographic Research, Rostock (Germany), June 18-19 2004.

England. Italian infant mortality reached the Swedish level only in recent years whereas Italian death rates at adult-old ages converged to Swedish levels more rapidly. Nevertheless, at the beginning of 70's, mortality is still higher in Italy than in Sweden at all ages. Both the countries were heavily affected by the Spanish flu in 1918 but while Italy was strongly involved in World War I and World War II, Sweden was neutral during both world wars.

For our purpose of modelling mortality surfaces and determining the impact of current conditions and that of early-life factors on adult and elderly mortality, data were needed not only for Italian and Swedish men and women aged 50-99 from 1950 onwards, but also for all the cohorts involved in the study period. More precisely, we analysed Swedish data from 1950 to 2006, accounting for mortality data of the cohorts born from 1851 to 1956, and Italian data from 1971 to 2006, accounting for mortality data of the cohorts born from 1872 to 1956.

Data requirements were also related to our choice to model period-cohort mortality rates so as to exactly match one single cohort and one single calendar year. These rates have been calculated taking annual deaths by Lexis triangles by age and sex, and annual population at January 1^{st} by age and sex. These data were obtained from the Human Mortality Database (www.mortality.org).

3. METHOD

Graphic representations of mortality surfaces as Lexis maps over age and time are a powerful tool for a first inspection of age, period and cohort effects and for descriptive purposes. Detailed analyses, however, demand analytical tools that can extract structural information from surfaces of mortality rates more accurately. Our final aim is to disentangle these surfaces in their period and cohort components.

3.1. *Model specification*

Mortality surfaces may be analyzed through various parametric specifications (Lee Carter, 1992; Vaupel, 1999) that may be seen as part of the general class of relational models and may be estimated using the maximum likelihood method. Also the model presented here may be considered as a relational model.

Let

$$\mu(x, y) = \mu_0(x, y) \cdot \exp[\alpha \cdot I_p(y) + \beta \cdot I_c(y - x)] \tag{1}$$

be the force of mortality at age x, $x = 1,..., m$ and time y, $y = 1,...,n$, where I_p and I_c are two indicators of period and cohort factors respectively, α and β measure the impact of these period and cohort indicators respectively, and $\mu_0(x,y)$ is a standard mortality surface, representing the general mortality trend. This two-dimensional baseline may be obtained through empirical observations or parametric functions.

Both the period and cohort factors may been synthesized through different mortality indexes representing life conditions and circumstances in the years (n) and the cohorts ($m+n-1$) involved in the study period. For comparative purposes, period and cohort indicators have been standardized so as to range from 0 to 1.

3.2. *Estimation procedure*

The inclusion of various components in fully parametric models can be carried out in different ways. However, identifiability and computational issues may arise, leading to unstable maximum likelihood estimates. For this reason, we follow a semi-parametric approach, by smoothing the standard mortality surface over age and time. Assuming that death counts are a realization of a Poisson distribution, we can use two-dimensional regression splines, specifically *B*-splines with penalties, known as *P*-splines, to describe the baseline $\mu_0(x,y)$ (Eilers and Marx, 1996; Currie, Durban and Eilers, 2004).

In order to describe behavior and features of the *P*-spline models we show an example in which data are simulated from a Normal distribution in a one-dimensional setting. First we compute a set of *B*-splines, $\boldsymbol{B}$, over the x axis as shown in figure 1. Each column of $\boldsymbol{B}$ contains a *B*-spline which assumes, over its row, a specific value for each x. In this way we can use such basis in a simple regression setting:

$$\boldsymbol{y} = \boldsymbol{B}\boldsymbol{a} + \varepsilon, \quad \varepsilon \approx N(0, \sigma^2)$$

where the coefficients $\boldsymbol{a}$ are associated to each *B*-spline and determine the heights of them. In such framework the following simple system of equations estimates the coefficient $\boldsymbol{a}$:

$$\hat{\boldsymbol{a}} = (\boldsymbol{B}'\boldsymbol{B})^{-1}\boldsymbol{B}'\boldsymbol{y} \; .$$

Outcomes for the simulated example are depicted in the right panel of figure 1. Obviously a large number of *B*-spline (20 in this case) would lead to over-fitting results. Instead of reducing the number of *B*-splines, Eilers and Marx (1996) suggested to penalize the coefficients in $\boldsymbol{a}$. In formula we estimate the coefficient as follows

$$\hat{\boldsymbol{a}} = (\boldsymbol{B}'\boldsymbol{B} + \boldsymbol{P})^{-1}\boldsymbol{B}'\boldsymbol{y} \tag{2}$$

where $\boldsymbol{P} = \lambda \boldsymbol{D}'_d \boldsymbol{D}_d$. The matrix $\boldsymbol{D}$ constructs dth order differences of $\boldsymbol{a}$. In this example and in the following, we assume $d = 2$. By changing the smoothing parameter λ smoothness can be tuned. Once λ is selected the system of equation in (2) has a unique solution. Automatic selection criteria such as cross-validation and Bayesian Information Criterion can be employed for optimizing λ.

Figure 1 illustrates the capability of *P*-splines in smoothing our simulated data for $\lambda = 10$. Note the different heights in the two panels: penalized coefficients $\boldsymbol{a}$

lead to smoothly changes in the *B*-splines heights, whereas if we let each coefficient free, the outcomes come obviously undersmooth.

P-spline models can be adapted easily for the class of Generalized Linear Models and, specifically, for Poisson-distributed mortality data. In the one-dimensional case, the following system of equations is solved iteratively:

$$\hat{\boldsymbol{a}}_{t+1} = (\boldsymbol{B}'\boldsymbol{W}\boldsymbol{B} + \boldsymbol{P})^{-1}\boldsymbol{B}'\boldsymbol{W}\boldsymbol{z}_t \tag{3}$$

where $\mathbf{W} = \mathrm{diag}(\boldsymbol{\nu})$ denotes the weight matrix and $\boldsymbol{z} = (\boldsymbol{d}\text{-}\boldsymbol{\nu})/\boldsymbol{\nu} + \boldsymbol{Ba}$ is the so-called working response. In case of mortality data the vector $\boldsymbol{d}$ is the vector of death counts, $\boldsymbol{\nu}$ is the expected death counts from the current model. Exposure population can be accommodated within this framework assuming death counts as product of the force of mortality and exposures.

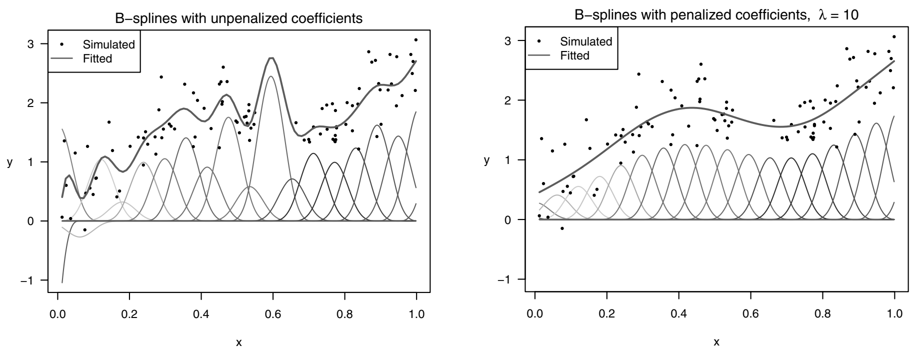

Figure 1 – Unpenalized (left panel) and penalized regression (right panel). Simulated data fitted using P-splines.

In order to model two-dimensional mortality data, we seek to construct a basis for two dimensional regression. For the purpose of regression, we suppose that the data are arranged as a column vector. Let $\boldsymbol{B}_x$ and $\boldsymbol{B}_y$ be regression matrices of *B*-splines based on age x and year y, respectively. The regression matrix for our two dimensional model is the Kronecker product

$$\boldsymbol{B} = \boldsymbol{B}_y \otimes \mathbf{B}_{\boldsymbol{x}}$$

In the spirit of the *P*-splines we use a relatively high number of *B*-splines over both domains. Therefore the smooth standard surface can be written as

$$\mu_0(x, y) = (\boldsymbol{B}_y \otimes \boldsymbol{B}_{\boldsymbol{x}})\boldsymbol{a} = \boldsymbol{Ba}$$

If there was not other additional covariates, such as the period and cohort indicator, equation (3) could be used for smoothing the standard mortality surface $\mu_0(x,y)$. Nevertheless the two-dimensional setting requires a different penalty term:

$$\boldsymbol{P} = \lambda_x(\Gamma_y \otimes \boldsymbol{D}_x'\boldsymbol{D}_x) + \lambda_y(\boldsymbol{D}_y'\boldsymbol{D}_y \otimes \Gamma_x) \tag{4}$$

where λ_x and λ_y are the smoothing parameters used for age and years, respectively. The matrices Γ_x and Γ_y are the identity matrix with dimension equal to the associated number of *B*-splines. The difference matrix D_x and D_y act over the two domains. We refer to Currie et al. (2004) for more details. In the following we use 15 and 17 *B*-splines for age and years, respectively. Bayesian Information Criterion will be used for selecting both λ_x and λ_y.

P-splines models can be seen as regression model and therefore further covariates can be included in a generalized version of the model matrix. With additional period and cohort indicators (with associated coefficients), we substitute in equation (3) the matrix $\boldsymbol{B}$ with the following design matrix $\boldsymbol{X}$:

$$\boldsymbol{X} = [\boldsymbol{B} : \boldsymbol{I_p} : \boldsymbol{I_c}]$$

where $\boldsymbol{I_p}$ and $\boldsymbol{I_c}$ are vectorized versions of the selected indicators. Obviously the position of the elements in the indicators must correspond to the position in the data structure. Moreover the penalty matrix $\boldsymbol{P}$ needs to be modified following a block-diagonal structure:

$$\boldsymbol{P}^{\text{final}} = \text{diag}(P, 0, 0),$$

since the coefficient α and β associated to the indicators do not need to be penalized.

This approach allows us to estimate simultaneously both the smooth baseline surface, and the period and cohort effects. In this way, we let the data speak by themselves using smoothing methods and without forcing any model structure which could influence the estimation of α and β.

3.3. *Choice of period and cohort indictors*

To evaluate the impact of early-life conditions versus that of current conditions on mortality later in life, we need to choose a period and a cohort indicator. Infant and child mortality are usually considered good proxies of early-life conditions in historical populations. Thus, we consider separately infant mortality (m_0) and child mortality ($m_{1\text{-}4}$) as cohort indicators. Following previous studies (Finch and Crimmins 2004, Barbi and Vaupel 2005, Myrskylä 2010b), also current conditions have been proxied by period infant mortality (figure 2).

However, this choice may be not optimal for representing period factors. Other synthetic indicators such as changes in the variability of the distribution of ages at death may be more suitable for describing current mortality conditions. Thus, taking into account that the transition from high to low mortality has been accompanied by significant compression of the distribution of ages at death, we consider Keyfitz's *H* as an alternative period indicator:

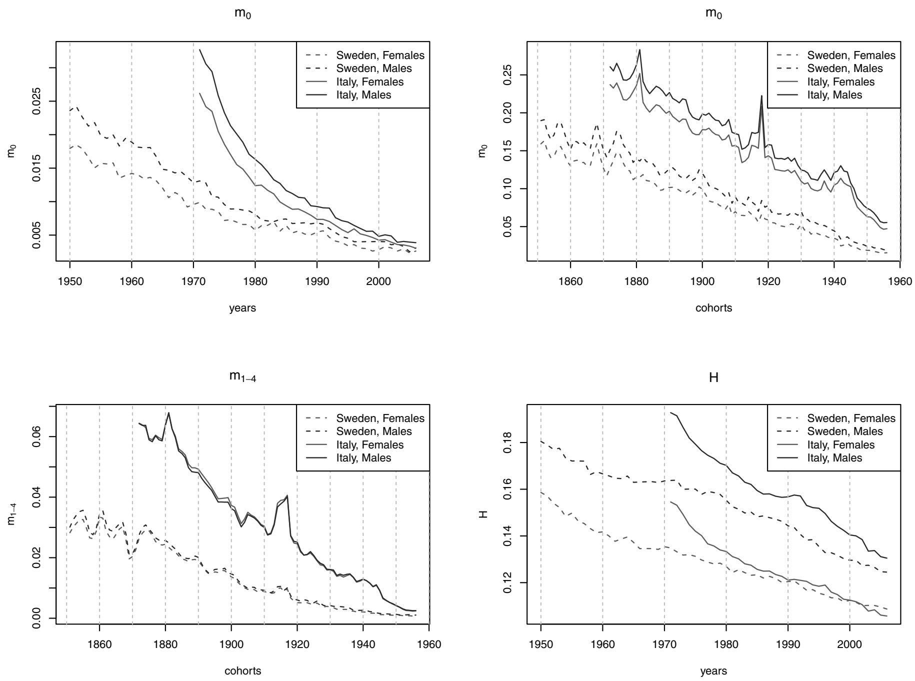

Figure 2 – Period and cohort indicators. Infant mortality (m_0) over years and cohorts (top panels). Child mortality ($m_{1\text{-}4}$) over cohorts (bottom-left panel), entropy measure (H) over years (bottom-right panel). Sweden and Italy, both sexes.

$$H = -\frac{\int_0^\infty S(x) \cdot \ln[S(x)]dx}{\int_0^\infty S(x)dx} \tag{5}$$

which is also known as a measure of entropy, and expresses the degree of concavity in the survivorship curve and the death concentration at older ages (figure 2).

4. RESULTS AND DISCUSSION

As a first step, following previous recent studies, we applied Model 1 considering infant mortality (m_0) as an indicator of both period and early-life conditions. Both in Sweden and in Italy results were not statistically significant (not shown). The only exception was for Italian men, where estimates of α and β, the period and cohort parameters, are set to very low negative values. This would mean that the impact of both early-life conditions and current circumstances on adult and elderly mortality, although statistically significant for men in Italy, is negligible in any case. Given our low confidence in the choice of the period indicator used here, these results are not surprising.

Consequently, Model 1 has been applied considering a measure of mortality compression, Keyfitz's H, as an indicator of period conditions (see Section 3.3). Results are shown in table 2 and figures 3-6. When the model is fitted to Swedish data, the only statistically significant estimate is that of the female period effect (α=-0.177) indicating that current conditions had a positive role in determining mortality reduction at adult and old ages. Although not statistically significant, one could speculate that the positive estimated values of the cohort effect for both women and men (β_{female}=0.032 and β_{male}=0.046) and, hence, the negative impact of early-life conditions on late-life mortality, might indicate the existence of debilitation effects for the cohorts involved in the study period. In Italy, estimates of α are statistically significant for both women and men and are set at much higher levels (α_{female}=-0.838 and α_{male}=-0.435) with respect to those found for Sweden. Furthermore, the impact of period effects is higher for women. As noted above, Sweden finds itself still at an advantage with respect to Italy in terms of survival. Italy, however, has caught up, especially during the last decades and particularly with respect to female mortality. Thus, the higher values (in absolute terms) of the α coefficient reflect this greater impact of period effects in Italy, and for women especially, that let Italy make up the lag with Sweden. The cohort parameter β is not statistically significant for Italian women but it is significant for Italian men. The estimated value is negative and set at a low level (β_{male}=-0.023) showing that cohort effects too had a positive, although modest, impact in lowering male mortality at older ages. As mentioned in Section 2, Italy, unlike Sweden, passed through two important negative events (besides the Spanish flu), World War I and World War II. Some studies found higher mortality at older ages for cohort involved in the conflicts at younger ages (Horiuchi 1983, Caselli and Capocaccia 1989). Thus, for Italian men especially, one might even expect some debilitation effects, that is a positive, rather than negative, value of the β parameter. However, it must be stressed that the model assumes that cohort effects, as well as period effects, are independent of age. This is perhaps a too simplistic assumption, especially for the cohort factor, as both selection and debilitation effects may act during the life-course and counterbalance out at older ages.

As a further step, we examined the influence of child mortality on late-life mortality. Results from Model 1 with $I_p=H$ and $I_c=m_{1\text{-}4}$ are shown in table 2 and figures 7-10. Estimates of α and β are set to about the same values obtained from the previous application of the model. The only difference is found for Italian women where the cohort parameter is now negative and statistically significant. However, its value is about one-tenth of the period coefficient, confirming thus the primary importance of current conditions.

TABLE 2

Estimated parameters α and β, with standard errors (in parenthesis).
We depicted in bold parameters statistically significant at 95%. Sweden (top) and Italy (bottom), both sexes

SWEDEN		Women		Men	
I_p	I_c	α	β	α	β
H	m_0	**-0.177** (0.0470)	0.032 (0.0226)	-0.067 (0.0426)	0.046 (0.0222)
H	$m_{1\text{-}4}$	**-0.177** (0.0470)	0.028 (0.0212)	-0.067 (0.0426)	-0.002 (0.0218)

ITALY		Women		Men	
I_p	I_c	α	β	α	β
H	m_0	**-0.838** (0.0316)	0.009 (0.0086)	**-0.435** (0.0306)	**-0.023** (0.0093)
H	$m_{1\text{-}4}$	**-0.838** (0.0316)	**-0.087** (0.0126)	**-0.434** (0.0306)	**-0.084** (0.0131)

Lastly, in order to check the presence of multicollinearity, we fit the model accounting only for the cohort indicator. Results (not shown) confirm the output of the full model for both the countries and sexes, that is the importance of the cohort indicator stays modest with respect to that of the period indicator in Italy whereas in Sweden estimates of β are not (or only weakly) statistically significant.

5. CONCLUSIONS

This study investigates the relative importance of period and cohort effects in adult and elderly mortality in Italy and Sweden in the second half of the 20^{th} century. For this purpose, we devised a two-dimensional semi-parametric model for mortality surfaces that produces good fit of the data and robust estimates of the period and cohort parameters. The findings of this study show that period effects have been of primary importance in the process of mortality reduction at adult and old ages observed in the last decades. The effects of early-life conditions are modest and often not statistically significant. These results are consistent with previous studies (Kannisto et al 1997, Myrskylä 2010a,b). However, since, as a first step, we assumed that the cohort parameter (as well as the period parameter) is independent of age, some doubts still remain on the direction of the action of these effects. Future research should therefore be conducted using more sophisticated models that overcome this assumption accounting for cohort (and period) effects that, more realistically, may change with age. This will hopefully help to further understand the role of selection and debilitation processes in mortality at older ages.

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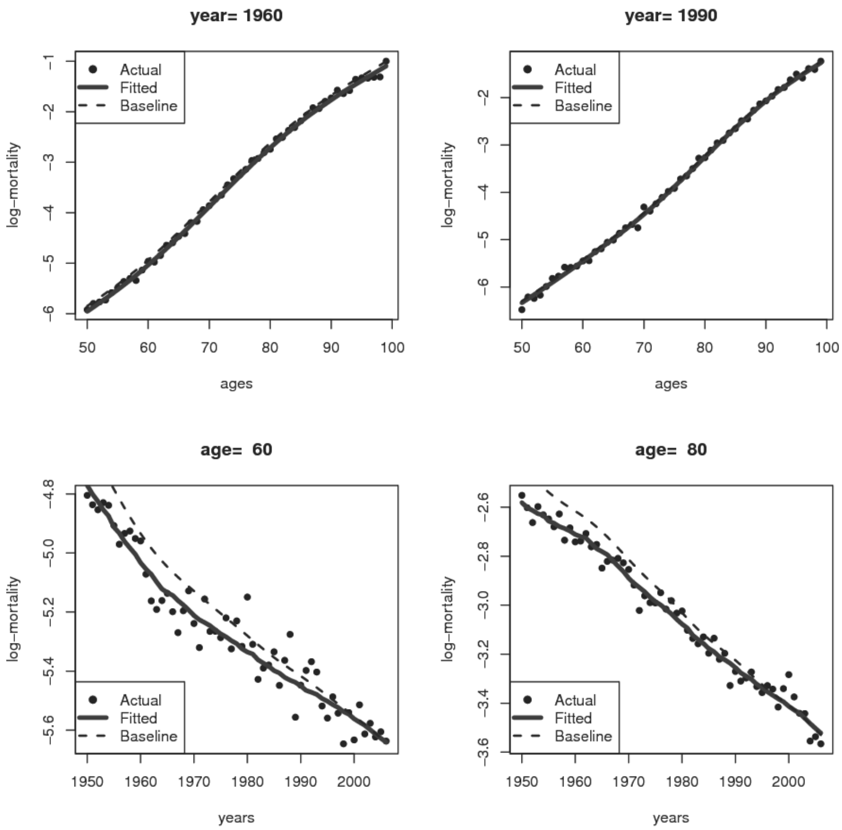

Figura 3 – Observed and fitted mortality rates for selected years and ages. $Ip=H$ and $Ic = m_0$. Sweden, women.

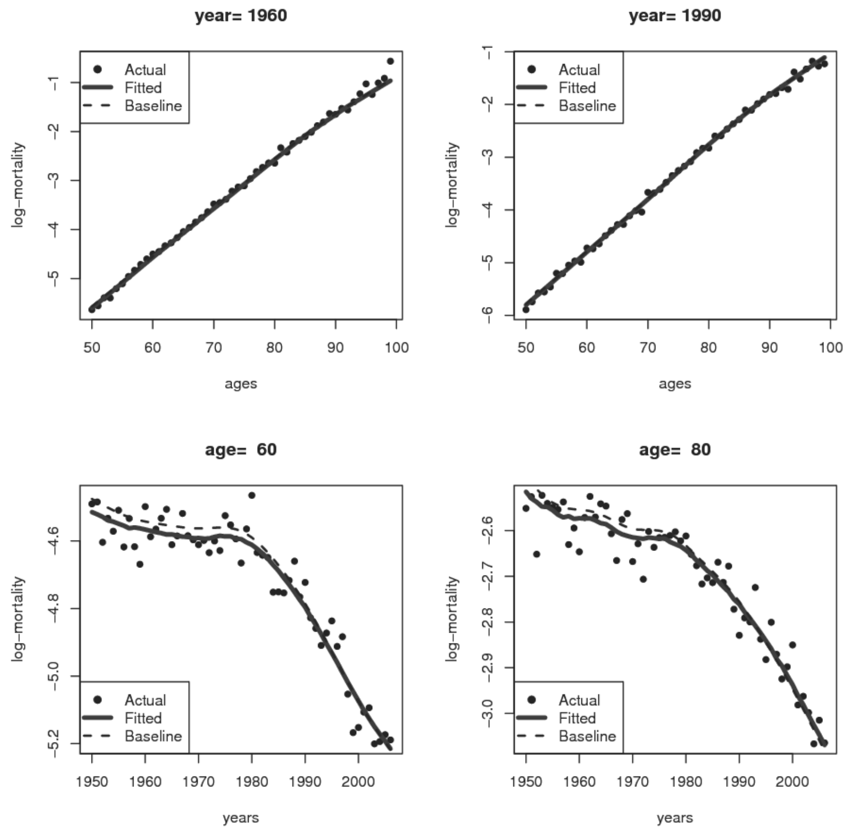

Figura 4 – Observed and fitted mortality rates for selected years and ages. Ip=H and Ic = m_0. Sweden, men.

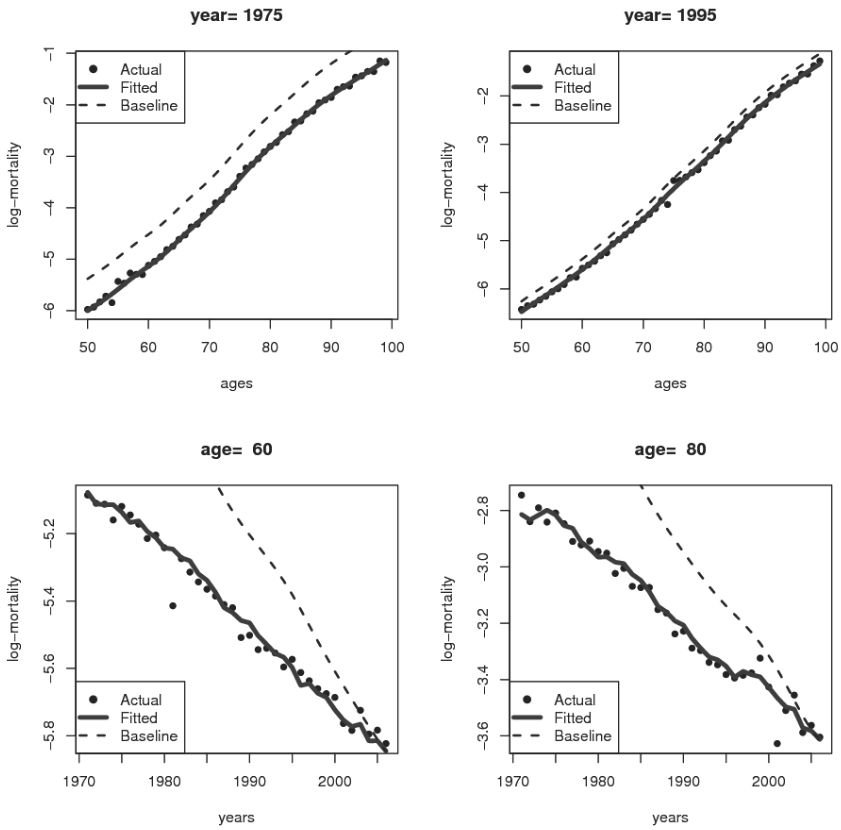

Figura 5 – Observed and fitted mortality rates for selected years and ages. Ip=H and Ic = m_0. Italy, women.

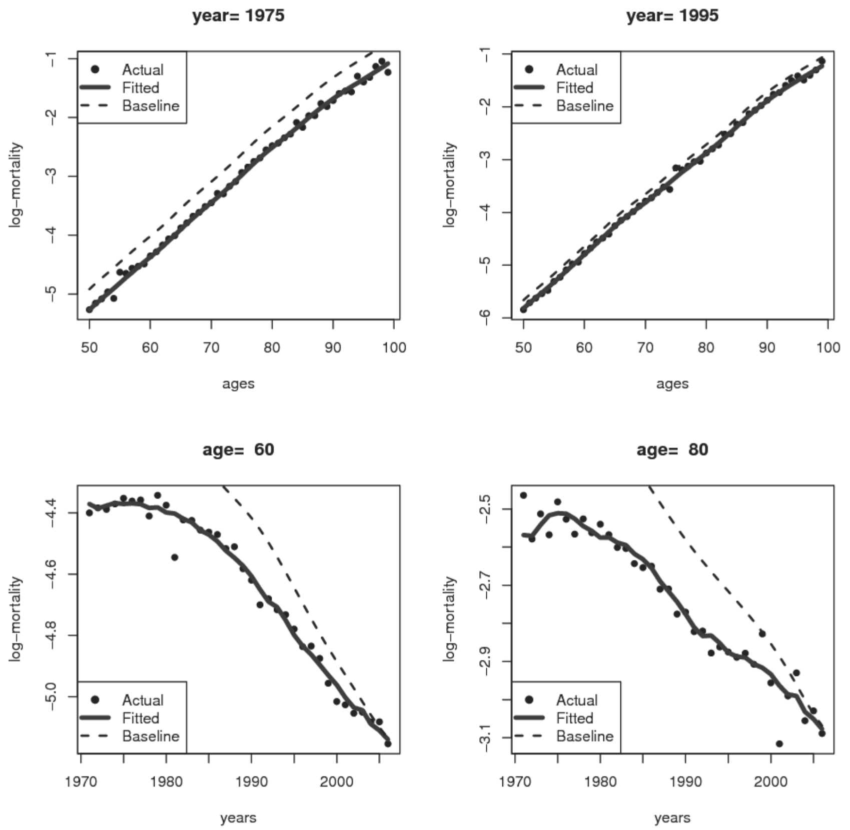

Figura 6 – Observed and fitted mortality rates for selected years and ages. Ip=H and Ic = m_0. Italy, men.

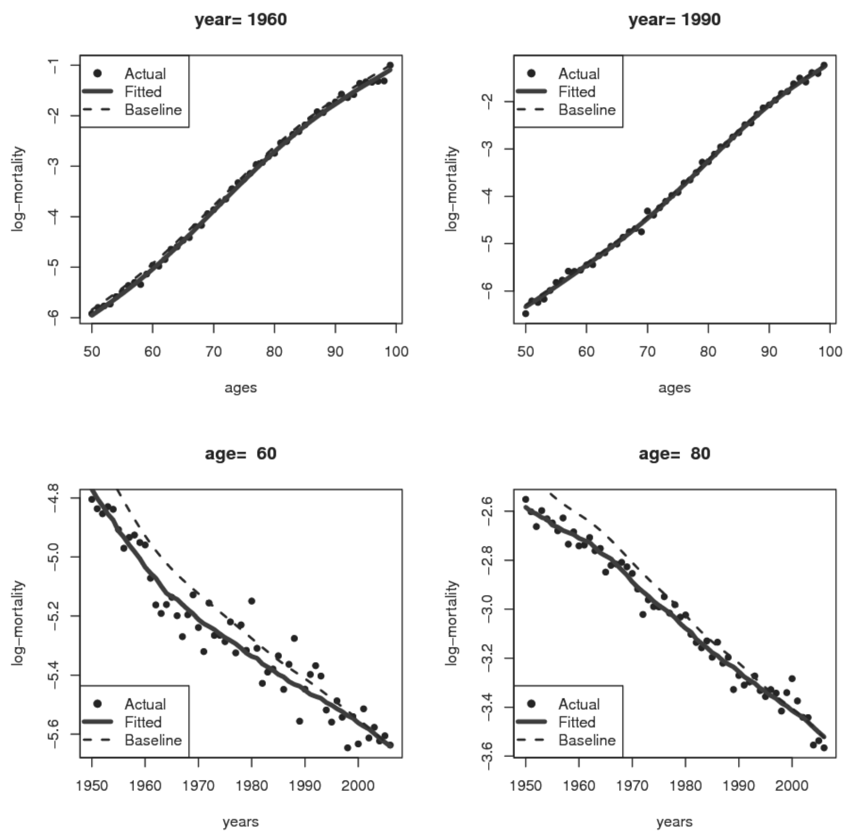

Figura 7 – Observed and fitted mortality rates for selected years and ages. $Ip=H$ and $Ic = m_{1\text{-}4}$. Sweden, women.

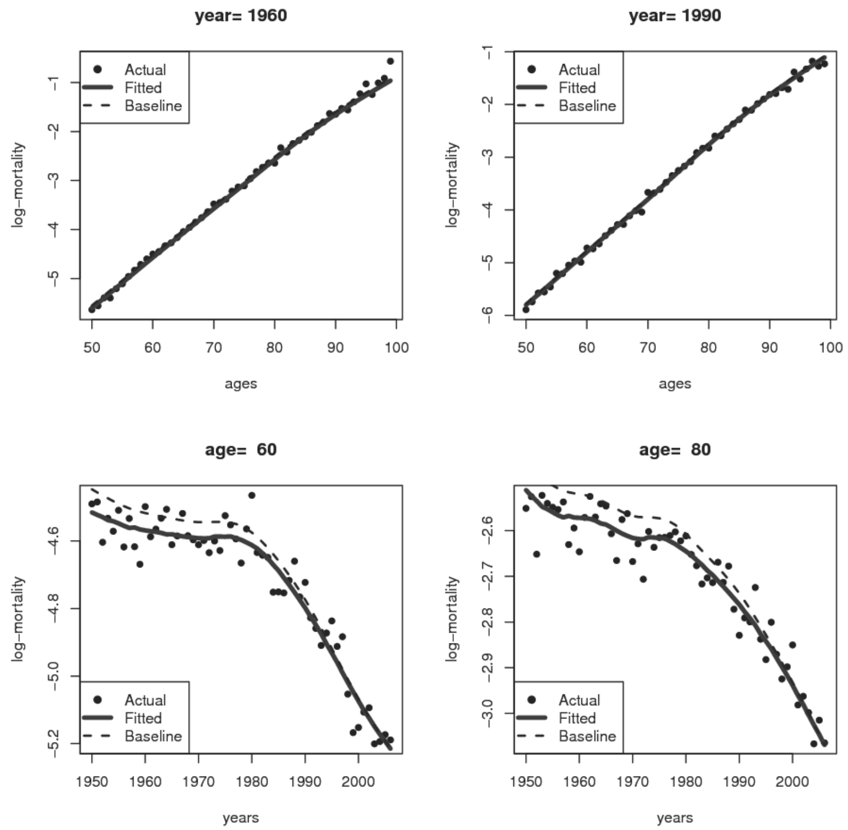

Figura 8 – Observed and fitted mortality rates for selected years and ages. *Ip*=*H* and *Ic* = $m_{1\text{-}4}$. Sweden, men.

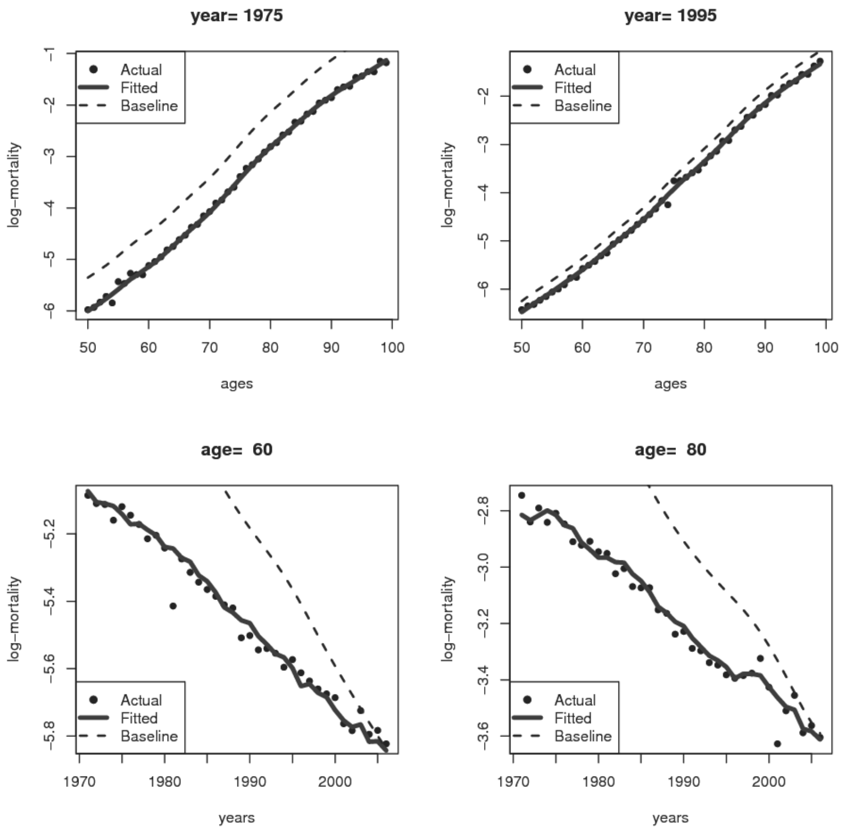

Figura 9 – Observed and fitted mortality rates for selected years and ages. Ip=H and Ic = $m_{1\text{-}4}$. Italy, women.

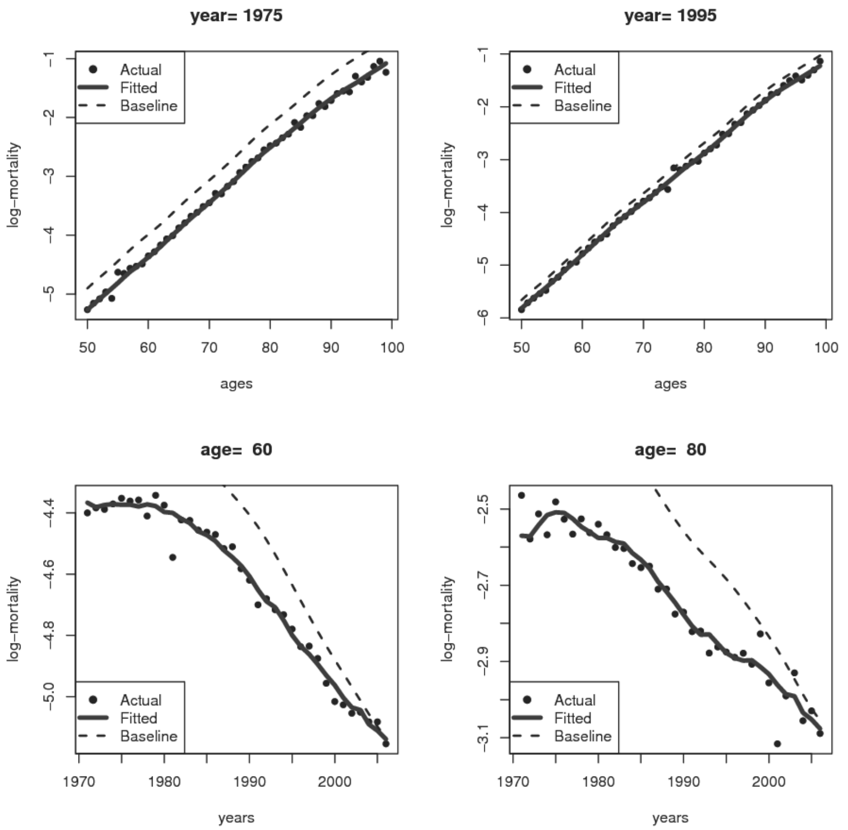

Figura 10 – Observed and fitted mortality rates for selected years and ages. *Ip*=*H* and *Ic* = $m_{1\text{-}4}$. Italy, men.

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SUMMARY

Period and cohort effects on elderly mortality: a new relational model for smoothing mortality surfaces

This study investigates the relative importance of period and cohort effects in adult and elderly mortality in Italy and Sweden in the second half of the 20^{th} century. For this purpose, we devised a two-dimensional semi-parametric model for mortality surfaces that produces good fit to the data and robust estimates of the period and cohort parameters. The findings of this study show that period effects have been of primary importance in the process of mortality reduction at adult and old ages observed in the last decades. The effects of early-life conditions are modest and often not statistically significant.