Early-life conditions, lifetime income and mortality risk in Italy*

Michele Belloni [†] Rob Alessie [‡] Adriaan Kalwij [§]

Abstract

In this study we examine differential mortality by income in Italy. We approximate individual's lifetime income with pension income. In addition, we obtain insights into the impact of early-life conditions on old-age mortality. We capture cohorts' life conditions by means of mortality rates at different early-life stages and exploit exogenous variation provided by a series of abrupt mortality events which severely affected specific cohorts. We account for non-linear cohort effects in the computation of life expectancy.

We find that in Italy differential mortality is less strong than in most other industrialized countries. The difference in life expectancy at age 65 between high-income and low-income males is about 1.7 years. For females, this difference is about 1.2 years. Early-life conditions have a long lasting effect on males' mortality, suggesting the existence of a "scarring effect": males grown in worse times have higher death probabilities at old-ages than those grown in better times. For females, we do not find a significant impact of early-life conditions on mortality. Finally, we show that by neglecting cohort effects in mortality the age profile is upward-biased thus leading to underestimation of life expectancy.

Keywords: early-life conditions, differential mortality, socioeconomic status, lifetime income

JEL codes: I1, I12

---

*The authors are grateful to G. Costa, C. Maccheroni, N. Vellekoop and the participants to the 2011 Netspar International Workshop and to the seminars at the Utrecht University School of Economics and the Medical School of the University of Turin for their useful comments. This research is funded by Netspar (Theme Project: "Pensions, Savings and Retirement Decisions II") and by Regione Piemonte (Bando Scienze Umane e Sociali 2008, Project "Aging, Labor Productivity and Sustainability of Public Pension Systems: an Investigation through Macro and Micro Modelling". All opinions and errors are those of the authors alone.

[†]University Ca' Foscari of Venice, CeRP - Collegio Carlo Alberto and Netspar. Address for correspondence: Via Real Collegio, 30, 10024 Moncalieri (TO), Italy, E-mail: belloni@cerp.unito.it

[‡]University of Groningen, Netspar and Tinbergen Institute

[§]Utrecht University School of Economics and Netspar

1 Introduction

Since the seminal work of Kitagawa and Hauser (1973) for the US, many empirical studies have quantified the difference in mortality risk across socioeconomic groups in various countries. Income, wealth or levels of education are used to proxy individuals' socioeconomic status (SES). A significant negative correlation between SES and mortality is nearly always found. The ratio of mortality risk of individuals in the lowest part of the income or wealth distribution over that of individuals in the highest part ranges from two in European countries to up to three in the US.[1]

The theoretical framework for most of the empirical studies on differential mortality by SES is given by the Grossman's model (Grossman 1972). According to it, individuals at the beginning of their life cycle are endowed with a stock of knowledge capital and health. Their stock of health depreciates over time and at a rate that decreases with knowledge capital. When it falls below a given threshold, individuals die. At the same time, knowledge capital positively affects income, e.g. through higher investments in education. These mechanisms result in a positive association between income and life expectancy.

Differential mortality by SES has important implications for pension policy (Whitehouse and Zaidi 2008). One of the most debated is related with the progressivity of pension systems. The retirement period is longer, and therefore pension wealth is higher, for longer-living individuals. The degree of redistribution of a pension system may be reduced or even reversed if richer individuals live longer than the poorer. Another key pension policy issue is pricing of retirement annuities and actuarial fairness (Brown 2002).

Very often the quantification of the gradient SES-mortality is given in terms of relative risks of death (like the ratios we mentioned in the first paragraph). The key information that policy makers needs to known is however life expectancy at retirement - more than relative death risks - by SES. Quantifying life expectancy is more data demanding than relative death risks, since one needs to model risks of death by age. A simplified way to obtain life expectancy by SES consists in applying death probabilities by age - obtained from external sources, such as official statistics - to computed

[1]See Kalwij, Alessie, and Knoef (2011) for the Netherlands, Attanasio and Emmerson (2003) for the UK, von H.M. Gaudecker and Scholz (2007) and Hupfeld (2009) for Germany; see Duleep (1986) and Attanasio and Hoynes (2000) for the US.

relative risks. This simplification can be misleading for two main reasons. First, it implicitly assumes that relative risks are constant by age. Second, the two components may refer to different populations: e.g. relative risks are computed for a population of workers or retirees whereas death probabilities by age refer to the overall populations. A proper way to compute life expectancy by SES is to include both age and a proxy of SES (e.g. income) as explanatory variables of mortality risk.

Models which explain mortality dynamics standardly include age, period and cohort (APC models). Age captures the biological process of human's body deterioration. Period controls for improvements in hygiene, public health and medical technology innovations as well as historical events and environmental factors (wars, famines, epidemics) which influence mortality of all society members (Omran 1982). Period effects influence the probability to die of individuals irrespective of age, in a reversible way, and for a short period of time (Caselli and Capocaccia 1989). The cohort component capture endogenous (e.g. genetic) and exogenous factors (e.g. malnutrition and inflammatory infections in utero and during early life) which influence the probability to die of individuals for a long period after the exposure.

Due to the perfect collinearity between age, period and cohort variables, APC models require additional restrictions for identification. A common solution is to impose an equality constraint on two (or more) adjacent age, period or cohort coefficients. Although such assumptions seem innocuous, their impact on the estimates may be dramatic (Ree and Alessie 2011) Mortality models which focus on differential mortality by socioeconomic status usually assume absence of cohort effects. In some cases a short time span covered by the data used in these studies does not permit disentangling time from cohort effects (e.g. Attanasio and Emmerson 2003, von H.M. Gaudecker and Scholz 2007). In other cases the authors are not interested in quantifying life expectancy or no attention was paid to the consequences of this assumption on its computation. Predicted life expectancies may be severely biased by omitting cohort variables, since age and cohort effects are mixed together. An alternative identifying strategy - which we pursue in this paper - is to approximate cohort effects by means of variables capturing socioeconomic conditions in which each cohort of individuals was born and/or grown.

There is an extensive literature evaluating the impact of individuals' early-life conditions on mortality at older ages. The risks of death over an individual's life cycle can be linked through "scarring" and/or "immunity" (Preston, Hill, and Drevenstedt 1998). Scarring determines a positive link across death risks at different ages. Certain diseases or conditions often acquired in childhood and at birth may permanently weaken the survivor and increase his probability to contract a disease and die at all subsequent ages.[2] Immunity leads to an inverse association across death risks over the life cycle. Individuals exposed to certain diseases such as influenza acquire immunization and might me expected to have a lower probability to contract similar diseases at subsequent ages.[3]

Various studies use mortality rates (in utero, at birth and during childhood) as indicators of cohort early-life conditions. The evidence is inconclusive. Kermack, McKendrick, and McKinlay (1934) reported that mortality up to age 15 correlate with subsequent cohort mortality in Great Britain and Sweden. Pearson (1912) discovered instead an inverse association between infant mortality and death rates from age 1 to 5 for England and Wales. Bengtsson and Lindström (2003), using historical data on parish registers in Sweden, find a positive and strong correlation between local infant mortality rate and mortality at ages 55-80 while do not find any effect of the disease load on mothers during pregnancy. Catalano and Bruckner (2006) find a positive relation between mortality at ages up to 5 and life expectancy at age 5 for Sweden, Denmark, England and Wales. Bruckner and Catalano (2009) report that the association between infant mortality and later mortality decreases with age, and disappears in adulthood. An interesting study for this paper is Caselli and Capocaccia (1989). These authors use Italian life table data for the cohorts 1882-1953 to study the relation between cohort mortality risk at birth and during childhood and mortality risk at ages 25-

[2] Many possible causal pathways connecting early life experiences and later mortality have been discussed (see Elo and Preston 1992). Barker (1994) and Barker (1995) suggested that preconditions for various diseases (e.g. coronary hearth disease, hypertension) are initiated in utero and become manifest much later in life (so called "fetal origin hypothesis"). Fridlizius (1989) suggested that exposure to certain infectious diseases (as smallpox) in the first 5 years after birth reduce immunity to other diseases and increase the risk of other infectious diseases in later life stages. Fogel (1994) proposes mechanisms based on malnutrition in utero and during early life and development of chronic diseases.

[3] At the population level, there can also be a "selection" effect, i.e. as a consequence of a bad event, weaker members of a cohort die, survivors are stronger and live longer. The effect of immunity and selection go in the same direction.

79. They find an age-varying effect: mortality risks are positively correlated up to age 45 and negatively correlated (but to a small extent, and only for males) at old ages.[4]

Due to lack of good data, the existing evidence on differential mortality by income in Italy is very limited.[5] Few epidemiological studies (e.g. Agabiti, Picciotto, and Cesaroni 2007, Agabiti, Picciotto, and Cesaroni 2008, Petrelli, Gnavi, Marinacci, and Costa 2006) exploit data available at metropolitan level to analyze morbidity and (often cause-specific) mortality differentials by income in some Italian cities. Results of these analysis have to be interpreted with caution since the data they are based on are not representative of the whole Italian population. The only nationwide study on differential mortality by income in Italy is provided by Leombruni, Richiardi, Demaria, and Costa (2010). This research is based on WHIP (Working History Italian Panel) data and reports evidence of limited relative risks by SES. Due to data limitations, Leombruni, Richiardi, Demaria, and Costa (2010) cannot properly quantify life expectancy at retirement by SES.

The contribution of this paper to the literature is twofold. First, we quantify differential mortality by income in Italy. As mentioned above, due to the lack of appropriate data, the evidence obtained so far for this country is very preliminary. Improving on Leombruni, Richiardi, Demaria, and Costa (2010), we calculate life expectancy at age 65 by income levels. Second, we obtain insights into the impact of early-life conditions on old-age mortality. We account for non-linear cohort effects in the estimation of the age profile and thus in the computation of life expectancy; this issue has been neglected in previous studies on differential mortality.

The quantification of mortality differential in Italy has been made pos-

[4]A recent series of studies show that the state of the business cycle at birth (van den Berg, Lindeboom, and Portrait 2006) and in the first years of life (van den Berg, Doblhammer, and Christensen 2009) are important determinants of later mortality. They also find that macroeconomic variables at birth other than the state of the business cycle do not contribute to explain death pathways. Finally, full life course epidemiology (see Kuh and Ben-Shlomo 1997, Ben-Shlomo and Kuh 2002) expands the links between early life and later mortality further to include the accumulation of risk through the full life course.

[5]There is some more, but still limited, evidence on differential mortality by education (see Maccheroni 2008, Mazzaferro and Savegnago 2008). Huisman and Kunst (2004) analyze SES inequalities in mortality among the elderly in 11 European populations. The Italian contribution is limited to the city of Turin. Results highlight that mortality differences across educational groups persist al old ages.

sible thanks to a new available pension file drawn from an administrative archive held by the main Italian Social Security Institution. This data reports all the pensions paid by INPS since its set up and until 2001. We have a precise proxy variable of the individual's lifetime income at our disposal, namely the amount of the pension benefit. The size of our data, which is pretty big until quite old ages, allows us to compute life expectancy at age 65. We capture cohorts' early-life conditions by means of mortality rates during childhood. We allow for different postnatal human development stages to have a different impact on old-age mortality. The cohorts we analyze (1901-1936) experienced an overall declining trend in mortality. Further variation is provided by a series of abrupt mortality events - such as the earthquakes of 1908 and 1915, the Word War I and the Spanish' flu of 1918 - which severely hit their childhood and adolescence lives.

The paper proceeds as follows. Section 2 presents the data, the sample selection and the main variables used in the empirical analysis. Section 3 describes the mortality risk model. Section 4 shows the main results and section 5 concludes.

2 Data and sample selection

2.1 Micro data

We exploit a pension file drawn from an administrative archive held by the main Italian Social Security Institution (INPS). It is a new file available for research scopes. It reports pensions paid by INPS since its set up and until 2001; it covers approximately 1/90 of the ex-private sector workforce plus social assistance beneficiaries (in total around 289,000 individuals). Civil servants are therefore not included. The first recorded pensions date back to the beginning of the XX century and were paid to voluntary enrolled private sector blue collar workers.

The data include all the pension schemes managed by INPS. Major schemes are the FPLD (covering private sector employees, paying 55 percent of the pensions recorded in the sample), and the schemes for the self-employed (artisans, traders and farmers, 22 percent of the sample). Special schemes managed by INPS cover e.g. miners, pilots, sailors, clerical personnel.[6] The following variables are available: month and year in which the

[6]The data also include information on pension schemes managed by non-INPS insti-

pension was first paid to the individual, month and year in which the pension flow ended (if ended), monthly amount (first payment), pension scheme and benefit type (e.g. old-age, early retirement, disability, survivors', social assistance benefits). In addition, there is information on the individuals date and region of birth and gender.

When an individual deceases, INPS records the end of all pension payments the person was receiving. We assume that the individual dies in the month of last payment by INPS. In case an individual obtains more than one pension during his life, this means that we look at the most recent ending date. In this way it is possible to sufficiently deal with some inaccuracy that could result from the existence of other possible reasons for stopping a specific pension payment, such as conversion of disability into old-age pensions, temporary illness or re-marrying (which terminates survivor benefits). We checked the level of accuracy of our reconstructed variable by computing death rates and comparing them with those from Human Mortality Database (HMD)[7] and we find that they are very close.[8]

2.2 Sample selection

Our estimation sample includes Italian-native ex-private sector employees aged 65 and older in the period 1979-2001. We include cohorts between 1901 and 1936. Individuals born before 1914 are only observed in the data at ages greater than 65.

The age selection (65+) is dictated by the data, which is on pension beneficiaries, and by the retirement rules applied to employees. Until 1994 males (females) could claim an old-age pension at age 60 (55). After a phase characterized by gradual increments, the minimum age for the old-age pension was set to 65 (60) for males (females) in 2001. Empirically, at age 65 almost everybody is retired in the analyzed period (Belloni and Alessie 2009).[9] Including individuals younger than 65 would have raised an

---

tutions (public sector, special schemes managed by big firms). However, this additional information is incomplete and limited to the period 1994-2001. We do not use it in our main empirical analysis; however we exploit it in a sensitivity analysis (note: sensitivity not included in this version).

[7]www.mortality.org

[8]Death rates computed in our data only slightly underestimate official death rates, especially for males. It should however be realized that the two populations are different, since we consider ex-workers whereas HMD includes the whole population.

[9]To facilitate comparisons, we apply the same age selection to both of the genders.

issue of sample self-selection: e.g. those with worse health status may have retired earlier and be over-represented.

Years before 1979 could not be considered in the econometric analysis. From a first introspective investigation it in fact appeared that the quality of the variable "date in which the pension flow ended" is rather poor before year 1979 (we find a big increase in the number of deaths in 1979 which is not present in official statistics). To be clear, if e.g. an individual claimed a disability pension in 1960 at age 50, he/she is included in the sample but his/her mortality probabilities are evaluated starting from age 69 (year 1979). We excluded pensions claimed before 1950 and individuals born before 1901 (0.4 percent of the sample) since the coverage of the pension system for private-sector employees was partial and participation was voluntary for them. Immigrants (less than 2 percent of the sample) are also excluded since we do not know their early-life conditions.

We proxy individuals' lifetime income by means of the amount of the pension benefit they receive. This is a good proxy variable if we restrict our analysis to ex-private sector employees. In their case, the pension formula summarizes the salient characteristics of the working career: (last) average wages and seniority (years of contribution to the scheme). For the same reason, we were forced to exclude the the self-employed.[10] Due to their pension rules, benefits they received for most of the period covered by the data were not informative on their lifetime earnings.[11]

A possible issue of underestimation of total pension income (and thus lifetime income) may arise for private sector employees who contributed to other pension schemes managed by non-INPS institutions during their working career. For example, if an individual partly worked in the private

[10]We include ex-employees who also receive self-employment pensions, provided that the latter is a minor part in their total pension income.

[11]Up to 1990, pensions of self-employed were contributory-based, and contributions paid were a low constant per-year sum. Thus, the big majority of the pensions claimed by the self-employed until 1990 were below the minimum pension and were subsidized. Starting from 1990, the pension benefits of self-employed have been earnings-related and are more informative on lifetime earnings. We find a confirmation of these facts in the data. The coefficient of variation of earnings is equal to 0.7 for the self-employed and to 2.6 for employees. We also compare the distribution of pension income before and after 1990: while before 1990 the self-employed were mostly situated in the lowest 2 quintiles, afterward they represent a relevant part of the central and highest quintiles. As a sensitivity analysis we also include the self-employed in the estimation sample and we find that results for the income gradient do not change.

and in the public sector for a sufficiently long period to accrue pension rights in both of the funds we underestimate his total pension income. We will evaluate the relevance of this issue in a sensitivity analysis (see footnote 6). The lifetime income which we correlate to death rates is the individual's income. It is possible that, especially for females, household's income better represents their socioeconomic status than individual's income.[12] In the literature there is evidence that individual's income, more than spouse's income, is correlated with mortality. Kalwij, Alessie, and Knoef (2011) find that partner's income is only weakly associated with mortality risk for women.

2.3 Demographic data

As previously outlined, we proxy cohort effects in mortality by means of mortality rates at young ages. We therefore merge the micro data on pension benefits described above with cohort-level demographic data.

Mortality rates by age and gender for the cohorts 1901-1936 are taken from Human Mortality Database. We first impute age x period t mortality probabilities (q_x^t) to each cohort (from q_x^t to q_x^{yob}, where $yob = t - x$ and $x = 0 \dots 15$). We then define $S_{x-y}^{yob} = \prod_{j=x}^{y} \left(1 - q_j^{yob}\right)$ as the (gender-specific) conditional survival probabilities from age x to age y for cohort yob.

Survival probabilities by cohort and gender are illustrated in figure 1 separately for the age groups 0 and 1-5 (top panel), 6-10 and 11-15 (bottom panel). The figure makes clear that the cohorts we analyze experienced an overall increasing trend in survival at all childhood ages. It also reveals a series of mortality peaks (see e.g. S 0), corresponding to some known

[12] Moreover, females are under-represented in the sample, since their participation in the labour market was lower than males'. In the estimation sample we do not account for survivor's benefits as a proxy for lifetime income. We carry out an empirical quantification of females' underrepresentation in the sample, by computing the percentage of females versus males by age in the sample and comparing these figures with corresponding values from HMD database. We find an underestimation of the percentage of females in our data by around 8 percentage points. Notice that, even if we included survivors' benefits beneficiaries in the analysis, females would be underrepresented. They would not be observed in the data if the following three conditions jointly occurred: a) they did not work enough to receive a pension, b) they are married and c) their husband died later than them. In other words, the data misses the group of married females belonging to households which income comes from the husband.

historical events, which halted this increase: the devastating earthquakes of 1908 and 1915, Word War I (1915-1918), the 1918 Spanish flu and the 1919-20 smallpox outbreak.

Mortality was very heterogeneous across Italian regions, especially in correspondence of the above outlined abrupt events. The 1908 earthquake hit Calabria and Sicily while in 1915 earth tremors shocked the Marsican area and the Abruzzi. The Spanish' flu epidemic affected mainly Central and Northern Italy, although some regions such as Liguria and Veneto were left relatively untouched (Pinnelli and Mancini 1999).

2.4 Variables definitions and descriptive statistics

The unit of time of our analysis is the calendar year. Age is defined at the 1st January of each year. The mortality risk it is the probability to die during the calendar year. The analysis is carried out separately by gender. The final estimation sample includes 594,784 observations for males and 522,023 observations for females. We observe 27,369 deaths for males and 14,938 for females, corresponding to unconditional death probabilities equal to 4.60 and 2.86 percent respectively.

Figure 2 show average mortality rates by age for selected cohorts (males and females). Mortality rates increase by age. The vertical distance between two lines at the same age can be interpreted as a first evidence of time/cohort effects in mortality. Overall, a declining trend in mortality over time/cohorts emerges for both of the genders. This trend is somewhat more pronounced for males than for females. This evidence finds a confirmation in survival curves (not shown, they can only be computed for cohorts younger than 1913 in the sample at age 65). For males, the cumulated probability to survive from age 65 until age 75 increases incessantly from 69 percent for the cohorts 1914-1916 up to 77 percent for the cohorts 1926-28. For females, this figure is equal to 85 percent for the cohorts 1914-16, it remains almost constant for the cohorts 1917-22, and only for younger cohorts it increases by 2 percentage points to reach a value of 89 percent for the youngest cohort.

Summary statistics for monthly pension income (2009 prices) are reported in table 1. Median pension income is equal to € 543 for males and € 360 for females. Mean values are € 1104 and € 567. In figure 3 we draw the average monthly pension income by age for selected cohorts. For each cohort, average pension increases by age only if poorer individuals die

Figure 1: Survival probabilities by cohort: males

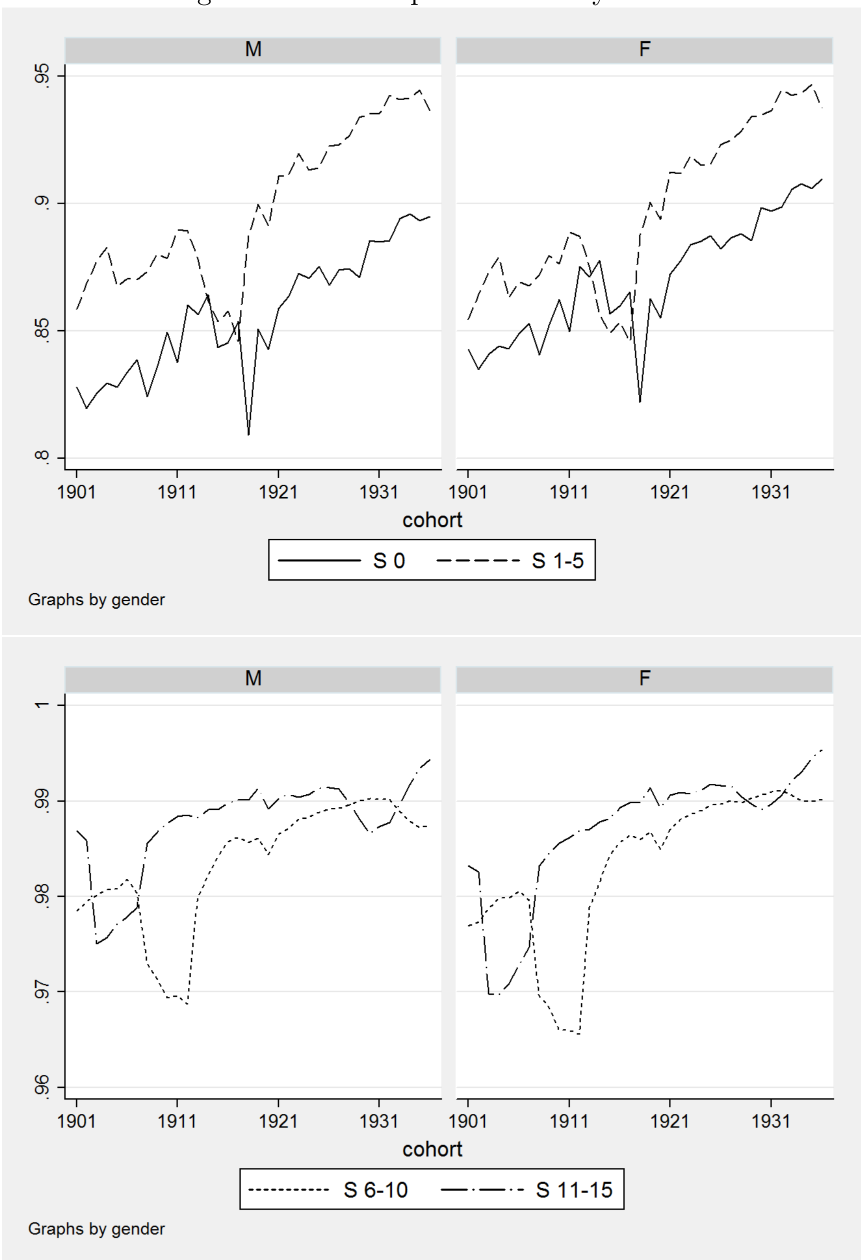


Figure 2: Average mortality rates by age for selected cohorts: males (top) and females (bottom)

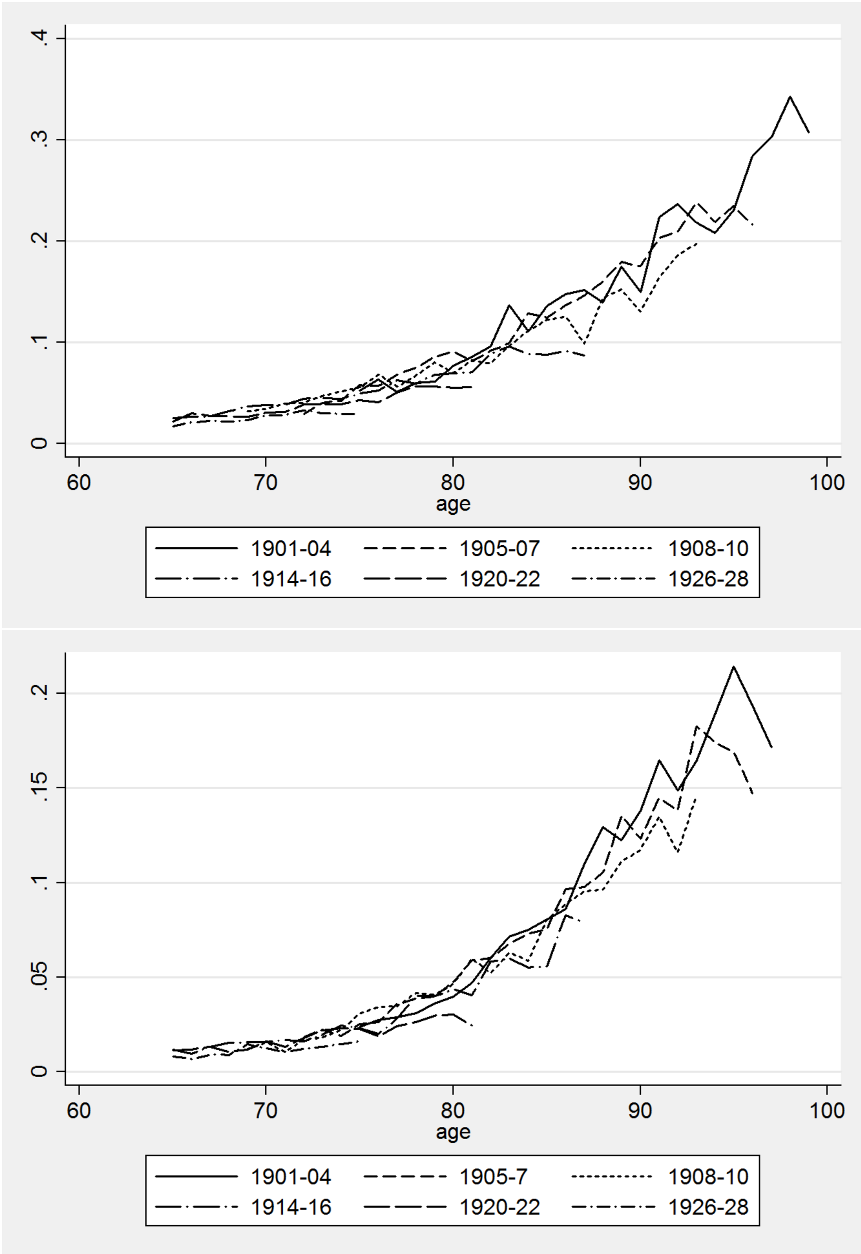
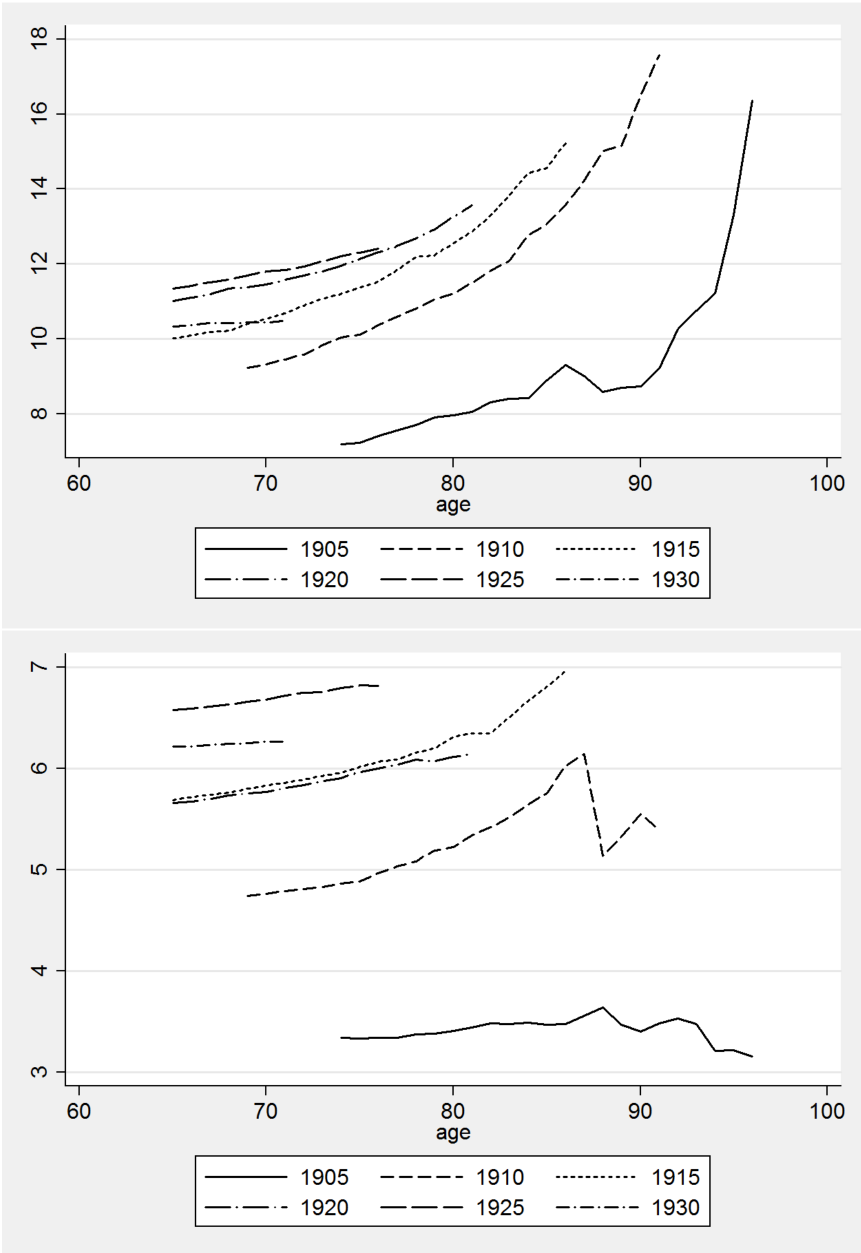


Figure 3: Average monthly pension income by age for selected cohorts: males (top) and females (bottom)



Notes: 100 euros, 2009 constant prices

Table 1: Monthly pension income: descriptive statistics

Statistic	**M**	**F**
Mean	1104	567
Std. Dev.	2693	1429
Skewness	11.45	15.47
Percentiles:		
10	256	217
25	340	276
50	543	360
75	1091	467
90	1912	781

Notes: euro, 2009 constant prices

before the richer. Curves are indeed generally upward-sloping, revealing evidence of differential mortality by income. The figure also shows marked differences across cohorts, due to both income growth over time and social security reforms. Important reforms were implemented during the 1990s, affecting pension income of the youngest cohorts. Mortality risk by cohort, age and income quartile are shown in the appendix.

3 Mortality risk model

Consider the following latent variable model for the mortality risk:

$$H_{it} = -\alpha_{t-yob_i} - \gamma_t - X_i\beta - \epsilon_{it} \tag{1}$$

where H_{it} is the individual's i stock of health at time t. We do not observe H_{it}, but we do observe M_{it}, where:

$$\begin{aligned} M_{it} &= 1 \quad \text{if} \quad H_{it} < 0 \\ M_{it} &= 0 \quad \text{otherwise} \end{aligned} \tag{2}$$

i.e. if the health stock of individual i at time t falls below a given threshold (normalized to zero in equation 1), we observe that the individual dies. α and γ are age and time-specific intercepts, X is a vector of time-invariant individual characteristics including year of birth and lifetime income, β a corresponding vector of parameters, and ϵ is an error term. Further, we assume that ϵ is i.i.d. across individuals and time, independent on all the r.h.s. variables and follows a logistic distribution with mean zero and variance $\pi^2/3$.

Therefore:

$$\Pr\left(M_{it}=1|\alpha_{t-yob_i},\gamma_t,X_i,M_{it-1}=0\right)=\Lambda\left(\alpha_{t-yob_i}+\gamma_t+X_i\beta\right) \tag{3}$$

where Λ is the logistic cumulative distribution function.

In the empirical specification, X_i includes pension income, cohort and region of birth. We parameterize model (1) as:

$$\begin{aligned}-H_{it}=\beta_0+\sum_{j=2}^{A}\alpha_j Dage(j)_{it}+\sum_{\tau=2}^{T}\gamma_\tau Dyear(\tau)_{it}+\sum_{c=2}^{C}\beta_c^1 Dyob(c)_i+\\+\beta^2\log(Y_i)+\sum_{r=2}^{R}\beta_r^3 Drob(r)_i+\epsilon_{it}\end{aligned} \tag{4}$$

where $Dage(j)_{it}$, $Dyear(\tau)_{it}$ and $Dyob(c)_i$ are a full set of age, year and year of birth dummies; A, T and C the number of ages, years and cohorts included in the sample; $\log(Y_i)$ is the logarithm of pension income approximating individual's i lifetime income and $Drob(r)_i$ is a full set of region of birth dummies.[13] The key parameters are β^2 and the α's. The former quantifies the association between lifetime income and mortality. The latter are used to predict life expectancy.

Due to the perfect collinearity between age, year, and year of birth variables, model (4) is not identified. Typically, APC models are identified by placing an equality constraint on two (or more) coefficients (this approach has been referred to as the CGLIM approach, see Yang, Fu, and Land (2004)). Imposing such constraints on even only two adjacent ages, periods or cohorts is sufficient to reach identification. Although such assumptions seem innocuous, their impact on the estimates may be dramatic (Ree and Alessie 2011). Moreover, in very few cases there is some a priori or external information on which one can rely to decide the restrictions to impose.

In the literature on differential mortality, typically cohort variables are ignored and there is no issue of identification. However, if cohort effects in mortality exist and they are not explicitly accounted for, they are captured by the age and year variables thus leading to inconsistent estimates for the α and the γ parameters (Ree and Alessie 2011). Specifically, if there are positive cohort effects, i.e. younger cohorts live longer than older ones, the

[13] The dummy variables are normalized, i.e. $Dage(1)_{it}=1$ if individual i at time t is the youngest individual in the sample.

estimates of α's are upward-biased and predicted life expectancy is likely downward-biased.

To break the perfect collinearity between APC variables in equation (4) - drawing from the extensive literature on the long-lasting effects of early-life conditions - we proxy cohort effects by means of cohort-level demographic variables, namely mortality rates during childhood (ages 0-15). We allow for different postnatal human development stages to have a different impact on old-age mortality. Specifically, we consider the following age periods separately: infancy (first year of life), preschooler (ages 1-5), primary school age (6-10), preteen-adolescence (11-15). Formally, we adjust model (4) in the following way:

$$
\begin{aligned}
-H_{it} = \beta_0 &+ \sum_{j=2}^{A} \alpha_j Dage(j)_{it} + \sum_{\tau=2}^{T} \gamma_\tau Dyear(\tau)_{it} \\
&+ \beta_0^1 \log(S_0^{yob_i}) + \beta_{1-5}^1 \log(S_{1-5}^{yob_i}) + \\
&+ \beta_{6-10}^1 \log(S_{6-10}^{yob_i}) + \beta_{11-15}^1 \log(S_{11-15}^{yob_i}) + \\
&+ \beta^2 \log(Y_i) + \sum_{r=2}^{R} \beta_r^3 Drob(r)_i + \epsilon_{it} \qquad (5)
\end{aligned}
$$

where $S_{x-y}^{yob_i}$ are (gender-specific) conditional survival probabilities from age x to age y for the cohort yob to which individual i belongs (see section 2.1) and β^1s are 4 unknown parameters capturing the effect of different child development stages on old-age mortality. Including a full set of dummy variables for region of birth is important for the consistent estimation of cohort effects. In the data section we mentioned that mortality in Italy has been very heterogeneous across regions. Controlling for regions of birth partly account for that.

As outlined in the introduction, early-life conditions may have an impact on later mortality in two ways: through "scarring" and/or "immunity". The two effects counteract, and empirically only the net effect can be identified. If the scarring effect prevails, the estimates of β^1s have a negative sign; viceversa they have a positive sign. The estimation of each β^1 exploits the (exogenous) variation over cohorts of the corresponding mortality rates (see figure 1). Figure 1 also shows that mortality rates at various child developments stages are not collinear thus allowing for a joint estimation of all β^1s.[14]

[14] We tried alternative specifications based on the cycle/trend decomposition of mortality

We also tested the *foetal* origins hypothesis (Barker 1994) by including in the model females mortality rates at fertile ages (between age 20 and 40) in the conception year. This additional variable should capture mothers' conditions during pregnancy. We find no evidence that intrauterine conditions affect mortality at old age. We also investigated the effect of socioeconomic conditions at birth on mortality. Unlike van den Berg, Lindeboom, and Portrait (2006), we do not find a significant effect of the state of the business cycle at birth. It should be recognized that most of the studies which find an effect of GDP at birth-type of variables on later mortality pertain to periods dating back to the XIX century or earlier, whereas we analyze mortality in more recent times.

Model (5) is entirely additive, i.e it rules out interactions of age, period and cohort (APC) variables each other and with respect to lifetime income. We experimented with a specification (as in Caselli and Capocaccia 1989) which includes a full set of interaction terms between $\log(Y)$ and APC variables, and we did not find joint significance for any of the three groups of interaction terms. In the introduction we stressed the importance of testing the assumption on the relationship between the socioeconomic gradient and age. The results of these tests (especially those regarding the interactions between $\log(Y)$ and age dummies) allow us to assume an age-constant income gradient.

4 Results

4.1 Main findings

Parameters estimates for the mortality risk model (1) are shown in tables 2 and 3 for males and females respectively. They present results for two specifications: I (where the effect of the $\log(S)$ variables is restricted to zero) and II, our main model based on (4)-(5). For the $\log(Y)$ variable, they also exhibit marginal effects (in italics).

The parameter estimate for the $\log(Y)$ variable is negative and significant at 1 percent level for both of the genders: as expected, lifetime in-

probabilities using the Hodrick-Prescott filter (with filter values 100 and 500). This is a well known approach in the literature (see Bengtsson and Lindström 2003, van den Berg, Lindeboom, and Portrait 2006, van den Berg, Doblhammer, and Christensen 2009, Myrskylä 2010). Results were very similar.

come is inversely correlated with death risk. Marginal effects provide a first quantification of this correlation. They suggest that a 1 percent increase in lifetime income (from its mean, i.e. from €1104 to €1115 for males and from €567 to €573 for females) reduces the mortality risk by 0.00437 percentage points for males and by 0.00318 percentage points for females. Illustrative predictions by income levels are provided in the next subsection.

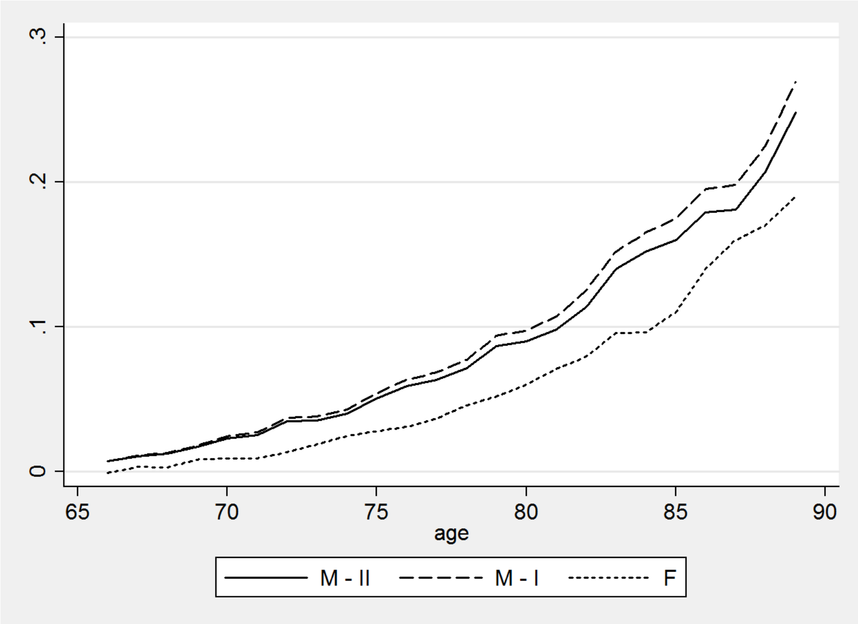
Early-life conditions have a long-lasting effect on male mortality. A likelihood-ratio test of spec. I against spec. II indicates joint significance for the $\log(S)$ variables ($\chi^2_{(4)} = 11.10$, p-value=0.0254). Between the child development stages included in the model, preschooler seem to matter the most to determine old-age mortality: the estimate of the $\log(S_{1-5})$ variable is highly significant (p-value=0.011). Also circumstances during primary school age are found important (the null $\beta^1_{1-5} = \beta^1_{6-10}$ is not rejected by a Wald-test). Negative signs for these two variables suggest the existence of a "scarring effect": individuals grown in worse times have higher death probabilities at old ages than those grown in better times. For females, we do not find a significant impact of the $\log(S)$ variables on mortality ($\chi^2_{(4)} = 1.91$, p-value=0.76).[15]

Figure 4 shows marginal effects by age and gender. For males, it compares spec. I (no cohort effects) and II. It turns out that, since there is evidence of scarring, the age profile is upward-biased if one does not account for cohort effects (in terms of trend, older individuals belong to older cohorts which spent their early-life in more difficult times).In turn, an upward-biased estimate of the age parameters may lead to underestimation of life expectancy (see predictions below).

We tested whether the $\log(S)$ variables completely capture nonlinear cohort effects. Following Kapteyn, Alessie, and Lusardi (2005) we estimated an augmented model which includes, in addition to the variables included in spec. II, a set of 30 year of birth dummies (35 cohorts from 1901 to 1956 minus 4 $\log(S)$ variables minus the reference category). The likelihood-ratio

[15]Results for females are in line with those in Caselli and Capocaccia (1989). For males these authors report evidence of a negative correlation across death risks over the life cycle for individuals aged 45 and older. However, the comparison with our results (age 65+) is difficult since they find an age-varying effect of early-life conditions on mortality. A tentative comparison can be made from figure 3 of Caselli and Capocaccia (1989). From this figure it looks that for ages 65+ the effect is very small; moreover, s.e. of the estimates are not reported in the paper.

Figure 4: Marginal effects by age



Note: reference category is age 65; the other variables are set at their sample means; for females results refer to model II

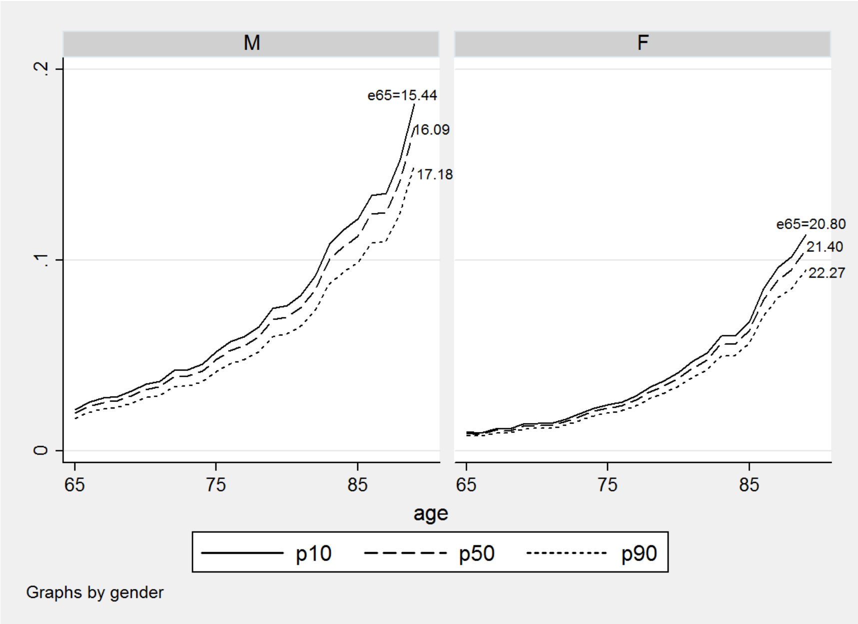
tests of this augmented model versus spec. II do not reject the hypothesis of no additional year of birth effects ($\chi^2_{(30)}$ = 28.88, p-value=0.52).

The time dummy coefficients highlight a declining mortality over the period 1979-2001. Results for the regional dummies highlight heterogeneity in old-age mortality across Italian regions. Males old-age mortality risk is highest in the North (Lombardy, Veneto, Friuli) and lowest in the South (e.g. Calabria, Basilicata, Molise, Sicily) with the exception of Campania. On the contrary, females live longer in the Centre of the country (e.g. Molise, Marche, Tuscany) and shorter in Campania and in Southern Italy (Sicily, Apulia, Calabria). These gender differences in mortality over the Italian territory are well documented (see ISTAT various years, Caselli, Peracchi, Balbi, and Lipsi 2003) and are typically attributed to different causes of death.

4.2 Model predictions

In this section we predict conditional death probabilities and life expectancies at age 65 (e_{65}) using the parameters estimates reported in tables 2 and 3.

Figure 5: predicted death probabilities by age and e_{65}: 10^{th}, 50^{th} and 90^{th} income percentiles



Note: representative individual is: year 1979, region of birth "Piedmont", cohort variables set at sample means

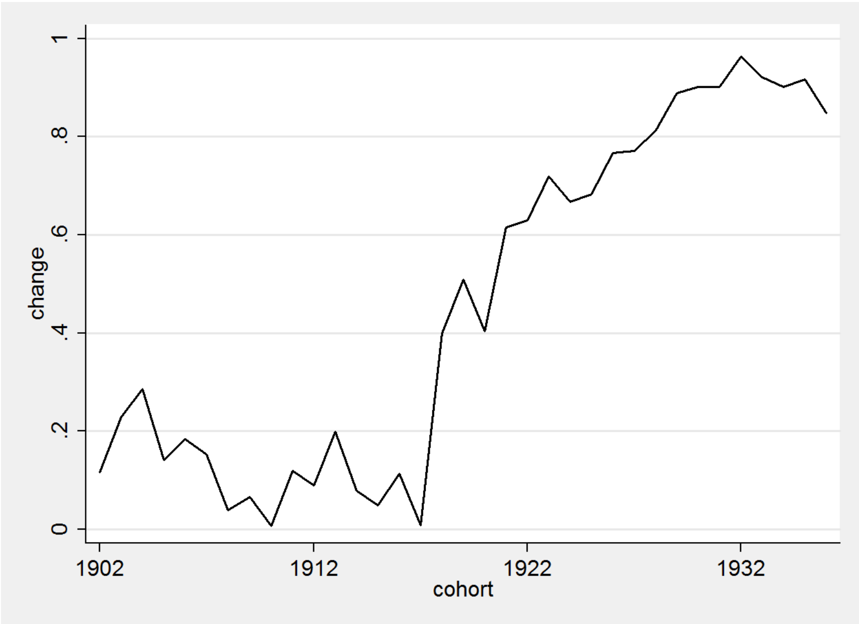
Figure 5 shows predicted death probabilities by age and e_{65} for the 10^{th}, the median and the 90^{th} percentile of the gender-specific income distribution, according to spec. II. For males (left panel) the relative death rates between the lowest and the highest illustrated percentiles are about 1.26. The corresponding difference in life expectancy is equal to 1.74 years ($e_{65} = 17.18$ years for p90 versus $e_{65} = 15.44$ for p10). For females we find a lower income gradient: relative death rates between the 10^{th} and the 90^{th} percentiles are about 1.22, corresponding to a difference in life expectancy at age 65 equal to 1.47 years ($e_{65} = 22.27$ years for p90 versus $e_{65} = 20.80$ for p10).[16] Spec. I, which provides upward-bias age parameters, predicts a lower life expectancy for males. According to this model, e_{65} is found equal to 15.46 years for the median income male (cf. with 16.09 years from spec. II).

Figure 6 finally reports the predicted change in e_{65} for males *due* to changes in their early-life conditions.[17] In comparison with the oldest cohort

[16] Relative death rates between the 25^{th} and the 75^{th} percentiles are equal to 1.15 for males and to 1.08 for females.

[17] In this simulation, we allow for the $\log(S)$ variables to vary by cohort, while keeping

Figure 6: Predicted change in life expectancy at age 65 due to changes in early-life conditions: males



Note: difference in years with respect to 1901 cohort; representative individual is: year 1979, region of birth "Piedmont", median income

in the data, younger cohorts live longer because of improved early-life circumstances. These improvements especially concern individuals born after the World War I, who experienced crucial improvements in living standards during their childhood with respect to the pre-war conditions. The figure highlights that the cohort of 1932 has the greatest benefit from improved early-life conditions: due to these changes, its e_{65} would be almost one year higher than that of the 1901 cohort.

5 Conclusions

In this study we examine differential mortality by income in Italy. Due to the lack of appropriate data, the evidence obtained so far for this country is very preliminary. This exercise has been made possible thanks to a new available pension file drawn from a social security administrative archive. We approximate individual's lifetime income with pension income. In addi-

all the other variables constant. Notice that, since we do not model time effects, we are not able to predict life expectancies by cohort.

tion, we obtain insights into the impact of early-life conditions on old-age mortality. We capture cohorts' life conditions by means of mortality rates at different early-life stages and exploit exogenous variation provided by a series of abrupt mortality events which severely affected specific cohorts. We account for non-linear cohort effects in the estimation of the age profile and thus in the computation of life expectancy.

We find that in Italy differential mortality is less strong than in most other industrialized countries. The difference in life expectancy at age 65 between high-income (90-th percentile of income distribution) and low-income (10-th percentile) males is about 1.7 years. For females, this difference is about 1.2 years. Early-life conditions have a long-lasting effect on males' mortality. Results suggest the existence of a "scarring effect": males grown in worse times have higher death probabilities at old-ages than those grown in better times. For females, we do not find a significant impact of early-life conditions. The impact on old-age mortality of the historical improvement in early-life conditions experienced by the cohorts in our sample - especially those born after the World War I - is considerable. A male born in 1932 alive at age 65 may expect to live 1 year longer than a male born at the beginning of the XX-th century due to improved early-life conditions. Finally, we show that by neglecting cohort effects in mortality the age profile is upward-biased thus leading to underestimation of life expectancy.

Table 2: Estimation results for males

	I			II		
dep.: dead	coef	se	aster	coef	se	aster
$\log(Y)$	-0.118	(0.00602)	***	-0.117	(0.00602)	***
	-0.00439	*(0.000223)*	***	*-0.00437*	*(0.000223)*	***
$\log(S_0)$				0.0430	(0.502)	
$\log(S_{1-5})$				-1.119	(0.442)	**
$\log(S_{6-10})$				-2.491	(1.628)	
$\log(S_{11-15})$				0.208	(2.583)	
age==66	0.182	(0.0478)	***	0.177	(0.0479)	***
age==67	0.263	(0.0473)	***	0.254	(0.0476)	***
age==68	0.306	(0.0471)	***	0.291	(0.0479)	***
age==69	0.410	(0.0464)	***	0.389	(0.0478)	***
age==70	0.525	(0.0457)	***	0.500	(0.0479)	***
age==71	0.574	(0.0458)	***	0.543	(0.0489)	***
age==72	0.728	(0.0450)	***	0.693	(0.0492)	***
age==73	0.742	(0.0454)	***	0.703	(0.0508)	***
age==74	0.814	(0.0454)	***	0.770	(0.0523)	***
age==75	0.959	(0.0449)	***	0.912	(0.0535)	***
age==76	1.066	(0.0448)	***	1.015	(0.0552)	***
age==77	1.117	(0.0453)	***	1.063	(0.0573)	***
age==78	1.208	(0.0454)	***	1.149	(0.0592)	***
age==79	1.360	(0.0455)	***	1.297	(0.0616)	***
age==80	1.390	(0.0467)	***	1.321	(0.0648)	***
age==81	1.468	(0.0477)	***	1.394	(0.0677)	***
age==82	1.600	(0.0483)	***	1.522	(0.0701)	***
age==83	1.792	(0.0484)	***	1.709	(0.0726)	***
age==84	1.871	(0.0497)	***	1.784	(0.0756)	***
age==85	1.927	(0.0515)	***	1.837	(0.0788)	***
age==86	2.042	(0.0532)	***	1.949	(0.0820)	***
age==87	2.051	(0.0571)	***	1.957	(0.0866)	***
age==88	2.196	(0.0598)	***	2.099	(0.0909)	***
age==89	2.411	(0.0623)	***	2.311	(0.0952)	***
age==90	2.282	(0.0722)	***	2.181	(0.104)	***
age==91	2.659	(0.0741)	***	2.556	(0.107)	***
age==92	2.788	(0.0852)	***	2.686	(0.117)	***
age==93	2.873	(0.101)	***	2.771	(0.131)	***
age==94	2.817	(0.128)	***	2.717	(0.153)	***
age==95	2.947	(0.154)	***	2.846	(0.176)	***
age==96	3.157	(0.185)	***	3.053	(0.204)	***
age==97	3.352	(0.239)	***	3.246	(0.254)	***
age==98	3.586	(0.360)	***	3.472	(0.370)	***

Aage_99_100	3.199	(0.575)	***	3.072	(0.581)	***
year==1980	0.153	(0.0572)	***	0.155	(0.0573)	***
year==1981	0.116	(0.0567)	**	0.120	(0.0569)	**
year==1982	0.0351	(0.0568)		0.0420	(0.0574)	
year==1983	0.188	(0.0546)	***	0.199	(0.0557)	***
year==1984	0.199	(0.0540)	***	0.214	(0.0558)	***
year==1985	0.138	(0.0539)	**	0.157	(0.0565)	***
year==1986	0.144	(0.0532)	***	0.167	(0.0569)	***
year==1987	0.146	(0.0527)	***	0.174	(0.0576)	***
year==1988	0.0730	(0.0528)		0.106	(0.0592)	*
year==1989	0.0934	(0.0522)	*	0.130	(0.0602)	**
year==1990	0.0541	(0.0522)		0.0954	(0.0618)	
year==1991	0.0361	(0.0520)		0.0818	(0.0634)	
year==1992	-0.0660	(0.0523)		-0.0160	(0.0655)	
year==1993	0.0129	(0.0515)		0.0672	(0.0667)	
year==1994	-0.00247	(0.0513)		0.0563	(0.0684)	
year==1995	-0.0406	(0.0513)		0.0229	(0.0703)	
year==1996	-0.138	(0.0517)	***	-0.0701	(0.0725)	
year==1997	-0.0898	(0.0512)	*	-0.0177	(0.0742)	
year==1998	-0.118	(0.0512)	**	-0.0414	(0.0762)	
year==1999	-0.128	(0.0511)	**	-0.0472	(0.0783)	
year==2000	-0.203	(0.0514)	***	-0.118	(0.0806)	
year==2001	-0.458	(0.0531)	***	-0.369	(0.0838)	***
region_ob==V Aosta	0.0214	(0.153)		0.0161	(0.153)	
region_ob==Liguria	-0.0725	(0.0438)	*	-0.0734	(0.0438)	*
region_ob==Lombardia	0.117	(0.0292)	***	0.116	(0.0292)	***
region_ob==Trentino A A	-0.0923	(0.0611)		-0.0915	(0.0611)	
region_ob==Veneto	0.0436	(0.0314)		0.0433	(0.0314)	
region_ob==Friuli V G	0.0256	(0.0448)		0.0267	(0.0448)	
region_ob==E Romagna	-0.0602	(0.0321)	*	-0.0606	(0.0321)	*
region_ob==Marche	-0.169	(0.0434)	***	-0.172	(0.0434)	***
region_ob==Toscana	-0.0506	(0.0328)		-0.0509	(0.0328)	
region_ob==Umbria	-0.220	(0.0532)	***	-0.221	(0.0532)	***
region_ob==Lazio	-0.0889	(0.0374)	**	-0.0893	(0.0374)	**
region_ob==Campania	0.0142	(0.0328)		0.0135	(0.0328)	
region_ob==Abruzzo	-0.222	(0.0458)	***	-0.224	(0.0458)	***
region_ob==Molise	-0.205	(0.0774)	***	-0.208	(0.0775)	***
region_ob==Puglia	-0.138	(0.0336)	***	-0.138	(0.0336)	***
region_ob==Basilicata	-0.227	(0.0575)	***	-0.226	(0.0575)	***
region_ob==Calabria	-0.266	(0.0387)	***	-0.266	(0.0388)	***
region_ob==Sicilia	-0.155	(0.0313)	***	-0.156	(0.0313)	***
region_ob==Sardegna	-0.221	(0.0450)	***	-0.221	(0.0450)	***
Constant	-3.149	(0.0706)	***	-3.319	(0.156)	***
Observations	594,784			594,784		

Log-likelihood	-105377.86	-105372.31
Specification tests (p-value):		
LR-test joint significance $log(S)$ vars.		0.0254
LR-test no additional cohort effects		0.52

Notes: the reference individual is aged 65, lives in year 1979 and is born in the region "Piedmont". *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Marginal effects (in italics) are computed at the sample means.

Table 3: Estimation results for females

	I			II		
dep.: dead	coef	se	aster	coef	se	aster
log(Y)	-0.155	(0.0109)	***	-0.155	(0.0110)	***
	-0.00318	*(0.000224)*	***	*-0.00318*	*(0.000225)*	***
log(S_0)				-0.0907	(0.718)	
log(S_{1-5})				-0.729	(0.566)	
log(S_{6-10})				-1.735	(1.712)	
log(S_{11-15})				-2.497	(2.551)	
age==66	-0.0475	(0.0819)		-0.0520	(0.0820)	
age==67	0.159	(0.0783)	**	0.150	(0.0786)	*
age==68	0.147	(0.0789)	*	0.133	(0.0798)	*
age==69	0.369	(0.0755)	***	0.350	(0.0771)	***
age==70	0.404	(0.0753)	***	0.379	(0.0779)	***
age==71	0.405	(0.0757)	***	0.376	(0.0795)	***
age==72	0.556	(0.0740)	***	0.521	(0.0793)	***
age==73	0.718	(0.0723)	***	0.678	(0.0792)	***
age==74	0.869	(0.0710)	***	0.824	(0.0800)	***
age==75	0.950	(0.0708)	***	0.899	(0.0819)	***
age==76	1.019	(0.0707)	***	0.964	(0.0842)	***
age==77	1.140	(0.0701)	***	1.080	(0.0860)	***
age==78	1.305	(0.0692)	***	1.240	(0.0877)	***
age==79	1.406	(0.0693)	***	1.335	(0.0908)	***
age==80	1.529	(0.0694)	***	1.452	(0.0941)	***
age==81	1.670	(0.0694)	***	1.587	(0.0972)	***
age==82	1.771	(0.0700)	***	1.683	(0.100)	***
age==83	1.946	(0.0696)	***	1.852	(0.103)	***
age==84	1.952	(0.0711)	***	1.853	(0.107)	***
age==85	2.083	(0.0714)	***	1.981	(0.110)	***
age==86	2.327	(0.0710)	***	2.221	(0.113)	***
age==87	2.468	(0.0722)	***	2.358	(0.116)	***
age==88	2.537	(0.0745)	***	2.423	(0.121)	***
age==89	2.663	(0.0768)	***	2.543	(0.126)	***
age==90	2.716	(0.0810)	***	2.592	(0.132)	***
age==91	2.994	(0.0828)	***	2.867	(0.136)	***
age==92	2.910	(0.0928)	***	2.779	(0.145)	***
age==93	3.194	(0.0971)	***	3.059	(0.150)	***
age==94	3.295	(0.109)	***	3.157	(0.160)	***
age==95	3.424	(0.125)	***	3.283	(0.173)	***
age==96	3.336	(0.156)	***	3.195	(0.198)	***
age==97	3.273	(0.196)	***	3.134	(0.229)	***
age==98	3.134	(0.257)	***	2.994	(0.283)	***

age==99	3.248	(0.322)	***	3.110	(0.343)	***
age==100	2.486	(0.735)	***	2.342	(0.745)	***
year==1980	0.110	(0.0979)		0.114	(0.0979)	
year==1981	0.0126	(0.0974)		0.0215	(0.0977)	
year==1982	0.117	(0.0934)		0.130	(0.0942)	
year==1983	0.203	(0.0905)	**	0.222	(0.0918)	**
year==1984	0.166	(0.0895)	*	0.190	(0.0918)	**
year==1985	0.123	(0.0887)		0.152	(0.0918)	*
year==1986	0.246	(0.0860)	***	0.281	(0.0906)	***
year==1987	0.228	(0.0852)	***	0.268	(0.0913)	***
year==1988	0.167	(0.0849)	**	0.213	(0.0928)	**
year==1989	0.142	(0.0843)	*	0.193	(0.0940)	**
year==1990	0.154	(0.0836)	*	0.209	(0.0953)	**
year==1991	0.0561	(0.0838)		0.116	(0.0975)	
year==1992	0.134	(0.0827)		0.199	(0.0987)	**
year==1993	0.0955	(0.0825)		0.165	(0.101)	
year==1994	0.0929	(0.0822)		0.167	(0.103)	
year==1995	0.102	(0.0818)		0.181	(0.105)	*
year==1996	0.00825	(0.0821)		0.0919	(0.108)	
year==1997	-0.0162	(0.0819)		0.0721	(0.110)	
year==1998	-0.0266	(0.0817)		0.0661	(0.113)	
year==1999	-0.0528	(0.0817)		0.0447	(0.115)	
year==2000	-0.0603	(0.0815)		0.0420	(0.118)	
year==2001	-0.439	(0.0839)	***	-0.332	(0.123)	***
region_ob==V Aosta	-0.0791	(0.258)		-0.0772	(0.258)	
region_ob==Liguria	-0.0527	(0.0589)		-0.0525	(0.0589)	
region_ob==Lombardia	-0.0499	(0.0339)		-0.0504	(0.0339)	
region_ob==Trentino A A	-0.121	(0.0713)	*	-0.122	(0.0713)	*
region_ob==Veneto	-0.165	(0.0389)	***	-0.165	(0.0389)	***
region_ob==Friuli V G	-0.0611	(0.0552)		-0.0624	(0.0553)	
region_ob==E Romagna	-0.151	(0.0374)	***	-0.151	(0.0374)	***
region_ob==Marche	-0.238	(0.0585)	***	-0.238	(0.0585)	***
region_ob==Toscana	-0.177	(0.0429)	***	-0.176	(0.0429)	***
region_ob==Umbria	-0.128	(0.0724)	*	-0.129	(0.0724)	*
region_ob==Lazio	-0.0140	(0.0488)		-0.0144	(0.0488)	
region_ob==Campania	0.0540	(0.0433)		0.0535	(0.0433)	
region_ob==Abruzzo	-0.148	(0.0722)	**	-0.148	(0.0722)	**
region_ob==Molise	-0.276	(0.134)	**	-0.279	(0.134)	**
region_ob==Puglia	-0.0251	(0.0438)		-0.0255	(0.0438)	
region_ob==Basilicata	-0.141	(0.0854)	*	-0.141	(0.0854)	*
region_ob==Calabria	-0.0496	(0.0497)		-0.0497	(0.0497)	
region_ob==Sicilia	0.0110	(0.0437)		0.0106	(0.0437)	
region_ob==Sardegna	-0.114	(0.0648)	*	-0.114	(0.0648)	*
Constant	-3.745	(0.114)	***	-3.922	(0.206)	***

Observations	522,023	522,023
Log-likelihood	-62380.59	-62379.64
Specification tests (p-value):		
LR-test joint significance $log(S)$ vars.		0.76
LR-test no additional cohort effects		0.16

Notes: the reference individual is aged 65, lives in year 1979 and is born in the region "Piedmont". *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Marginal effects (in italics) are computed at the sample means.

Appendices

Table 4: Mortality risk by cohort, age and income quartile: males

Cohort:			1901-1907					1908-1913		
Age	Q1	Q2	Q3	Q4	Q1/Q4	Q1	Q2	Q3	Q4	Q1/Q4
65-69						3.5	3	3.4	2.5	1.4
70-74	4.4	3.4	4.8	3.2	1.4	4.5	4.6	4.2	3.7	1.2
75-79	6.1	6.2	6.9	6.3	1	7	6.4	6.9	5.4	1.3
80-84	10.1	10.1	9.8	9.2	1.1	9.3	9.2	8.8	8.2	1.1
85-89	15.9	14.5	14.9	13.4	1.2	12.3	12	12.1	11	1.1
90-94	21.4	17.4	20.9	21.1	1	14.6	15.6	16.2	13.4	1.1
95+	22.5	30.1	21.6	29.9	0.8					
All	13.4	13.6	13.2	13.8	1	8.5	8.5	8.6	7.4	1.2
Cohort:			1914-1919					1920-1924		
Age	Q1	Q2	Q3	Q4	Q1/Q4	Q1	Q2	Q3	Q4	Q1/Q4
65-69	3.3	2.8	2.9	2.2	1.5	3.2	2.4	2.5	2	1.6
70-74	4.5	4.1	3.9	3.6	1.2	4.1	3.7	3.5	2.6	1.6
75-79	6.4	5.8	5.5	4.9	1.3	5	4.6	5	3.8	1.3
80-84	8.2	7.5	8.1	6.6	1.2	4.8	5.4	7.1	4.8	1
85-89	9.5	8.6	10	7.4	1.3					
90-94										
95+										
All	6.4	5.8	6.1	5	1.3	4.3	4	4.5	3.3	1.3
Cohort:			1925-1929							1930-1936
Age	Q1	Q2	Q3	Q4	Q1/Q4	Q1	Q2	Q3	Q4	Q1/Q4
65-69	3	2.1	2	1.4	2.1	2.2	1.8	1.8	1.4	1.6
70-74	3.1	3.3	3	2.5	1.3	2	2.3	2.2	1.9	1
75-79	3.7	3.9	3.1	3	1.3					
80-84										
85-89										
90-94										
95+										
All	3.3	3.1	2.7	2.3	1.4	2.1	2	2	1.6	1.3

Table 5: Mortality risk by cohort, age and income quartile: females

Cohort:			1901-1907					1908-1913		
Age	Q1	Q2	Q3	Q4	Q1/Q4	Q1	Q2	Q3	Q4	Q1/Q4
65-69						1.4	1.6	1.3	0.9	1.6
70-74	2.4	1.6	2.6	1.7	1.4	2	1.7	1.8	1.8	1.1
75-79	3.8	3	2.5	3.2	1.2	3.9	2.9	3.8	3.3	1.2
80-84	6.7	5.2	6.1	5.8	1.2	5.9	6	5.6	4.7	1.3
85-89	11.7	10.3	9.6	8.6	1.4	8.9	8	8.9	8.8	1
90-94	16	14.3	17.1	14	1.1	11.5	10.7	12.4	12	1
95+	17.4	20.7	14.2	17.5	1					
All	9.7	9.2	8.7	8.5	1.1	5.6	5.2	5.6	5.2	1.1
Cohort:			1914-1919					1920-1924		
Age	Q1	Q2	Q3	Q4	Q1/Q4	Q1	Q2	Q3	Q4	Q1/Q4
65-69	1.4	1.2	1.4	0.9	1.5	1.6	1	1	0.8	2
70-74	2.3	2	1.8	1.4	1.7	2.3	1.8	1.5	1.2	1.9
75-79	3.6	3.2	2.5	2.6	1.4	2.7	2.3	1.8	2.2	1.3
80-84	5.4	5.1	4.1	4	1.4	2.7	2.7	2.9	3	0.9
85-89	6.5	8.4	5.9	7.1	0.9					
90-94										
95+										
All	3.9	4	3.1	3.2	1.2	2.3	2	1.8	1.8	1.3
Cohort:			1925-1929							1930-1936
Age	Q1	Q2	Q3	Q4	Q1/Q4	Q1	Q2	Q3	Q4	Q1/Q4
65-69	1.3	0.9	0.7	0.7	1.8	1.1	0.7	0.8	0.7	1.6
70-74	1.7	1.2	1.2	1.2	1.4	0.9	0.7	0.6	1	0.9
75-79	1.9	1.6	2.2	1.3	1.4					
80-84										
85-89										
90-94										
95+										
All	1.6	1.2	1.4	1.1	1.5	1	0.7	0.7	0.8	1.2

References

Agabiti, N., S. Picciotto, and G. Cesaroni (2007): "The Italian Study Group on Inequalities in Health Care. The influence of socioeconomic status on utilization and outcomes of elective total hip replacement: a multicity population-based longitudinal study," *International Journal for Quality in Health Care*, 19(1), 37–44.

——— (2008): "The Italian Study Group on Inequalities in Health Care. The association of socioeconomic disadvantage with postoperative complications after major elective cardiovascular surgery," *International Journal for Quality in Health Care*, 62(10), 882–889.

Attanasio, O., and C. Emmerson (2003): "Mortality, health status and wealth," *Journal of the European Economic Association*, 1(4), 821–850.

Attanasio, O., and H. Hoynes (2000): "Differential Mortality and Wealth Accumulation," *The Journal of Human Resources*, 35(1), 1–29.

Barker, D. (1994): *Mothers, Babies, and Disease in Later Life*. British Medical Journal Publishing.

——— (1995): *Fetal origins of coronary heart disease*. British Medical Journal Publishing.

Belloni, M., and R. Alessie (2009): "The importance of financial incentives on retirement choices: New evidence for Italy," *Labour Economics*, 16(5), 578–588.

Ben-Shlomo, Y., and D. Kuh (2002): "A life course approach to chronic disease epidemiology: Conceptual models, empirical challenges, and interdisciplinary perspectives," *International Journal of Epidemiology*, 31, 285–293.

Bengtsson, T., and M. Lindström (2003): "Airborne infectious diseases during infancy and mortality in later life in southern Sweden, 1766-1894," *International Journal of Epidemiology*, 32, 286–294.

Brown, J. (2002): "Differential Mortality and the Value of Individual Account Retirement Annuities," in *The distributional aspects of social security and social security reform*, ed. by M. Feldstein, and J. B. Liebman, NBER, chap. 10, pp. 401–456. The University of Chicago Press, Chicago.

Bruckner, T., and R. Catalano (2009): "Infant mortality and diminished entelechy in three European countries," *Social Science & Medicine*, 68(9), 1617–1624.

Caselli, G., and R. Capocaccia (1989): "Age, Period, Cohort and Early Mortality: An Analysis of Adult Mortality in Italy," *Population Studies*, 43(1), 133–153.

Caselli, G., F. Peracchi, E. Balbi, and R. Lipsi (2003): "Differential Mortality and the Design of the Italian System of Public Pensions," *Labour*, 17(0), 45–78, Special issue.

Catalano, R., and T. Bruckner (2006): "Child mortality and cohort lifespan: a test of diminished entelechy," *International Journal of Epidemiology*, 35(5), 1264–1269.

Duleep, H. (1986): "Measuring Income's Effect on Adult Mortality Using Longitudinal Administrative Record Data," *Journal of Human Resources*, 21(2), 238–251.

Elo, I., and S. Preston (1992): "Effects of Early-life conditions on adult mortality: A review," *Population Index*, 58(2), 186–212.

Fogel, R. (1994): "The relevance of Malthus for the study of mortality today: Long-run Influences on health, mortality, labour-force participation and population growth," in *Population, Economic Development, and the Environment: The Making of Our Common Future*, ed. by K. Lindvall, and H. Landberg, pp. 231–84. Oxford University Press, Oxford and New York.

Fridlizius, G. (1989): "The deformation of cohorts: nineteenth century mortality in a generational perspective," *Scandinavian Economic History Review*, 37, 3–17.

Grossman, M. (1972): "On the Concept of Health Capital and the Demand for Health," *Journal of Political Economy*, 80(2), 223–255.

Huisman, M., and Kunst (2004): "Socioeconomic inequalities in mortality among elderly people in 11 European populations," *Journal of Epidemiology and Community Health*, 58, 468–475.

HUPFELD, S. (2009): "Rich and healthy-better than poor and sick?: An empirical analysis of income, health, and the duration of the pension benefit spell," *Journal of Health Economics*.

ISTAT (various years): "Annuario Statistico Italiano," .

KALWIJ, A., R. ALESSIE, AND M. KNOEF (2011): "The Association Between the Individual Income and Remaining Life Expectancy at the Age of 65 in the Netherlands," NETSPAR discussion paper n. 09/2009-033.

KAPTEYN, A., R. ALESSIE, AND A. LUSARDI (2005): "Explaining the Wealth Holdings of Different Cohorts: Productivity Growth and Social Security," *European Economic Review*, 49, 1361–1391.

KERMACK, W., A. MCKENDRICK, AND P. MCKINLAY (1934): "Death rates in Great Britain and Sweden: Some general regularities and their significance," *Lancet*, 226, 698–703.

KITAGAWA, E., AND P. HAUSER (1973): *Differential mortality in the United States: a Study in Socioeconomic Epidemiology*. Harvard University Press, Cambridge, MA.

KUH, D., AND Y. BEN-SHLOMO (1997): *A Life Course Approach to Chronic Disease Epidemiology*. Oxford University Press.

LEOMBRUNI, R., M. RICHIARDI, M. DEMARIA, AND G. COSTA (2010): "Aspettative di vita, lavori usuranti ed equit del sistema previdenziale. Prime evidenze dal Work Histories Italian Panel," *Epidemiologia e Prevenzione*, 34(4), 150–158.

MACCHERONI, C. (2008): "Disuguaglianze nella durata della vita per grado d'istruzione in Italia all'inizio degli anni 2000," Carlo F. Dondena Centre for Research on Social Dynamics, Bocconi University, working paper series n.3.

MAZZAFERRO, C., AND M. SAVEGNAGO (2008): "Differential Mortality and Redistribution in the Italian Notional Defined Contribution System," CAPPaper n. 47.

MYRSKYLÄ (2010): "The effects of shocks in early life mortality on later life expectancy and mortality compression: A cohort analysis," *Demographic Research*, 22(12).

Omran, A. (1982): "Epidemiological Transition: Theory," in *International Encyclopedia of Population: volume 1*, ed. by J. Ross, pp. 172–175. Free Press, New York.

Pearson, K. (1912): "The intensity of natural selection in man," in *Proceedings of the Royal Society of London*, B, pp. 469–476. The Royal Society.

Petrelli, A., L. Gnavi, C. Marinacci, and G. Costa (2006): "Socioeconomic inequalities in coronary heart disease in Italy: A multilevel population-based study," *Social Science & Medicine*, 63, 446–456.

Pinnelli, A., and P. Mancini (1999): "Mortality Peaks in the Late 19th and Early 20th centuries: Trend by Age and Sex," *European Journal of Population*, 14, 333–365.

Preston, S., M. Hill, and G. Drevenstedt (1998): "Childhood conditions that predict survival to advanced ages among African-Americans," *Society, Science & Medicine*, 47(9), 1231–1246.

Ree, J. D., and R. Alessie (2011): "Life Satisfaction and Age: Dealing with Underidentification in Age - Period - Cohort Models," *Social Science & Medicine*.

van den Berg, G., G. Doblhammer, and K. Christensen (2009): "Exogenous determinants of early-life conditions, and mortality later in life," *Social Science & Medicine*, 68(9), 1591–1598.

van den Berg, G., M. Lindeboom, and F. Portrait (2006): "Economic conditions early in life and individual mortality," *The American Economic Review*, 96, 290–302.

von H.M. Gaudecker, and R. Scholz (2007): "Differential Mortality by Lifetime Earnings in Germany," .

Whitehouse, E. R., and A. Zaidi (2008): "Socio-Economic Differences in Mortality: Implications for Pensions Policy," OECD Social, Employment and Migration Working Papers, No. 71.

Yang, Y., W. Fu, and K. Land (2004): "A Methodological Comparison of Age-Period-Cohort Models: Intrinsic Estimator and Conventional Generalized Linear Models," *Sociological Methodology*, 34, 75–110.