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Working paper

Projecting health trajectories in Europe using microsimulation

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ATHLOS

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Abstract

This working paper presents an innovative methodological framework for projecting the health of individuals with a set of risk factors using a microsimulation model. The model developed, called ATHLOS-Mic, projects the health of cohorts born before 1960 and a set of risk factors for the horizon 2060 for some European countries. It simulates the lives of individuals using statistical models that explicitly take into account interactions between the different dimensions, either biological and behavioral risk factors (smoking, obesity, depression, arterial hypertension and physical activity), socioeconomic characteristics (education), a health metric, and mortality. Using data from SHARE-HD, we used parameters from statistical models to project dynamically changes in risk factors with a set of covariates and their impact on a health metric. The health metric is then used to modulate the probability of survival. A set of analytical scenarios are built showing the effect of each risk factors on future health trajectories. Results show that driven by a better educational attainment, each generation will be healthier than the previous one at same age. In average, an individual of our base population will live about 18 more years, but only 5 in good health. The scenario removing the effect of having a low level of education on the health metric is the one having the largest effect on both the projected average health metric, the average number of years lived per person, and the average number of years lived in good health. Summing up, removing all risk factors would add 2 years of life, but 6 years in good health.

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1. Introduction

With the unavoidable aging of the population, the question of how healthy the population will be gains importance for policy makers. Indeed, since age is a risk factor for most diseases (Niccoli & Partridge 2012), more people with adverse health conditions necessitating special needs and treatments are expected from an increasing share of elderly. However, biological consequences of aging are not static. Several studies showed that not only the population lives longer than before, but lives also healthier (Salomon et al. 2012; Sanderson & Scherbov 2008; Sanderson & Scherbov 2015), thus re-questioning the age-threshold of what is "old" becomes necessary. Indeed, there are more and more evidences that confirm the famous popular phrase saying that "sixty is the new forty", as people aged 60 and over are in better health than before, but also have life habits that were before generally observed among younger population (Helmkamp & Carter 2009; Minkin 2016). The importance of distinguishing age and health is moreover important, since there are differences in the biological and molecular mechanisms of aging among individuals (Wagner et al. 2016). Most population projections traditional forecast the population under demographic characteristics only (age and sex), but the inclusion of additional dimension such as education (Lutz et al. 2014) and sociocultural variables (Bélanger et al. 2019) is an emerging approach in social sciences, first because it provides additional relevant outputs for public policies as well as for other analytical issues, and second because it increase the overall quality of the population projection by taking into account more source of heterogeneity (Bélanger et al. 2019; Lutz & KC 2011).

This working paper describes a microsimulation model aiming at projecting the health of elderly and a set of risk factors for a selection of European countries, and presents some preliminary examples of possible analytical scenarios. It's part of the EU-funded ATHLOS Project, which aims to achieve a better understanding of ageing by identifying patterns of healthy ageing trajectories, the determinants of those patterns, the critical points in time when changes in trajectories are produced, and to propose timely clinical and public health interventions to optimize healthy ageing. The microsimulation model developed, called ATHLOS-Mic, is built over a previous microsimulation model called CEPAM-Mic[1], which already includes 12 socio-economic dimensions, namely country of residence, age, sex, education, region of birth, duration of stay, age at immigration, education of the mother, religion, language and their interactions.

2. Measurement of health

The World Health Organization defined health in its preamble constitution as "a state of complete physical, mental and social well-being and not merely the absence of disease or infirmity" (WHO 1946), which can be measured by looking at the prevalence of health conditions in a population. However, a simple count of the number of chronic conditions does not take into account their severity, neither their impact on the well-being (Callahan 1973; Cieza et al. 2014). Moreover, the implication of stating "complete" and "absence" in the definition basically gives the status of unhealthy to everyone for most of their life (Huber et al. 2011; Idler 1993).

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[1] CEPAM-Mic has been conceived to study alternative migration scenarios and their consequences for future population trends in the European Union. It has been developed for the Centre of Expertise on Population and Migration (CEPAM), a joint research project of the International Institute for Applied Systems Analysis (IIASA) and the Joint Research Centre (JRC) of the European Commission.

As there is no unique indicator of true, underlying health status of individuals, a large body of research across disciplines often use various objective and subjective health measures such as chronic illness, the levels of physical and/or cognitive capabilities, self-assessment of health state as an instrument. Among these measures, many scholars rely on self-reports as a reasonable measures of overall health (Benyamini & Idler 1999). Typically, the self-rated health (SRH) is collected through a survey asking to report the overall health on a scale. Although being statistically associated with morbidity and mortality, this indicator is however influenced by some unrelated factors such as age, quality of life, attitudes and culture (Smith & Goldman 2011). In consequence, this measurement of health is poorly adapted for international or inter-groups comparisons (Benyamini 2016; Krause & Jay 1994). Furthermore, self-reported measures of health may suffer from a certain degree of reporting error due to a number of reasons (see Murray and Chen (1992)). For example, survey respondents' assessment on their health may be affected by their expectations of their own health, their use of healthcare and their comprehension of the actual survey questions asked (Bago d'Uva et al. 2008) or they can intentionally misreport their health state if there is a clear financial incentive to do so.
In our analysis, as a measure of overall health of individuals, we use a composite index of health developed by Caballero et al. (2017) as a part of the ATHLOS project. The construction of the health metric is based on the assumption that there exists a latent measure of the health of individuals in a sample that can be inferred from a set of observed health-related characteristics. More specifically, using Bayesian Item Response Theory, the distribution of a health score is estimated in a way that it reflects the distribution of the observed health status (represented by the health-related characteristics) of a particular sample.
Under this approach, health status is conceptualized as a vector of functioning in different domains ranging from simple to complex (e.g., vision, walking, kneeling, Activities of Daily Living, Instrumental Activities of Daily Living). The approach is in line with the notion of health status suggested by the World Health Organization: (i) an intrinsic attribute of an individual that can be aggregated to the population level; and (ii) comprising domains of human functioning that describe the actual impact of health conditions on people's lives. In particular, an individual i belonging to a group j that has a health score θ_{ij}has a probability of having a health characteristic k such that:

$$P\left(H_{kji} = 1 \middle| \theta_{ij}\right) = \phi(a_{kj}\theta_{ij} + b_{kj}) \qquad (1)$$

where H_{kji} is a dummy variable which reflects whether or not individual i in group j has health characteristics $k, \phi()$ is the c.d.f. of the standard normal distribution, and where

$$a_{kj} \sim \mathrm{N}(1, \omega_a^2) \qquad (2)$$
$$b_{kj} \sim \mathrm{N}(\mu_b, \omega_b^2) \qquad (3)$$

are group-specific "discrimination" and "difficulty" parameters, respectively. The discrimination parameter is related to how the likelihood of having a particular health condition k decreases with the health metric θ_{ij}, while the difficulty parameter represents how likely it is to have a particular health characteristic k.
The health metric θ_{ij} has random group and individual-group components:

$$\theta_{ij} = u_j + e_{ij} \qquad (4)$$
$$u_i \sim N(0, \sigma_{L1}^2), e_{ij} \sim N(0, \sigma_{L2}^2) \qquad (5)$$

The values of $\omega_a^2, \mu_b, \omega_b^2, \sigma_{L1}^2$ and σ_{L2}^2 are estimated using a Bayesian multilevel item-response theory (IRT) approach on a set of health characteristics including self-reported health questions and measured tests obtained from the longitudinal household surveys. Posteriorly, the uni-dimensionality of these health variables used in the estimation of the metric are assessed by, first, conducting an Exploratory Factor Analysis (EFA) to detect the latent structure among the items and, second, applying a Confirmatory Factor Analysis (CFA) to gather evident for creating a global health score.

The health metric was developed and first presented in Caballero et al. (2017) using 6 waves of the English Longitudinal Study of Ageing (ELSA) from 2002 to 2012, and further expanded in De la Fuente et al. (2018) for a joint panel of 6 waves of ELSA and 11 waves (years 1992-2012) of the Health and Retirement Study (HRS). In the latter version, the group variable j is set to describe whether the individual belongs to the ELSA or the HRS sample as not all health characteristics are observed in both studies. In particular, 45 health characteristics are observed in ELSA, while only 30 of these characteristics are also observed in HRS (see De la Fuente et al. (2018)).

The novelty of this measure lies chiefly in the ability to simultaneously capture many aspects of individual health to back up a population-based distribution of health. Unlike other measures commonly used in the literature, this health metric is obtained as a continuous variable (range from 0 to 100), and therefore, does not suffer from the problems associated with the either objective or subjective discretization of health in different categories (e.g. self-rated health or ADL indexes, see Benitez-Silva and Ni (2008) for a detailed analysis of these measures). Moreover, it does not suffer from the reporting error observed both in subjective and objective health measures.

3. Projection based on ATHLOS-Mic by IIASA

3.1 Description of the microsimulation model ATHLOS-Mic

The microsimulation model developed by IIASA is called ATHLOS-Mic. It is built over the CEPAM-Mic model, which is already suitable for a multidimensional population projection including notably age, sex, and education. ATHLOS-Mic consists into the implementation of health module that adds health-related variables, namely a health metric and some risk factors, into a specific module that is applied to cohorts born before 1961 and living in selected countries.

3.1.2 Data

A consistent and rigorous modeling of health for projection purposes in European countries required parameters that will model the relationship between individual’s health and its socioeconomic, biological and behavioral determinants. The modeling thus depends on the availability of data. Up to now, the Survey of Health, Ageing and Retirement in Europe (SHARE) is the most complete dataset that can be used for this kind of model. This cross-national panel survey interviewed more than 120,000 individuals aged 50 and over in European countries. Moreover, this survey is included the harmonized dataset (HD), built in the context of the ATHLOS project, which standardizes a set of health-related variables for scientific studies provided by many international and national surveys, comprising a health metric derived from a large set of health-related questions and corresponding to the definition stated in the previous section. Variables found in the HD are thus comparable in their definition and share reference formats. Five waves of SHARE covering 2004 to 2013

are included in the HD, but the third wave is designed for other purpose and doesn't include variables of interest for our study, which leaves us with 4 usable waves.
Although SHARE is one of the most comprehensive survey for the older population in Europe, it still includes a lot of data limitations that restrict the projection opportunities:

- First, only the population aged 50 or older are surveyed. For projection purposes, it limits the projected population to these cohorts only, because no information on health and risk factors are available on younger cohorts.
- Second, it does not cover all the countries in the European Union. 18 countries have participated to at least one wave, but the participation to at least 2 waves is necessary to have longitudinal data allowing the estimation of transition rates. Only 14 countries meet this requirement, which are showed in table 1 with their respective samples size.
- Third, even for countries participating to more than one wave, an important attrition is observed, as in any longitudinal survey. The number in parenthesis in Table 1 represents the retention rate of individuals surveyed in the previous wave (including deceases that are reported).
- Finally, to be included in a transition model, individuals need to have non-missing values for the interest variable as well as for covariates in two consecutive waves. Since a certain proportion of missing values is observed for all variables, the usable sample size for specific models is reduced.

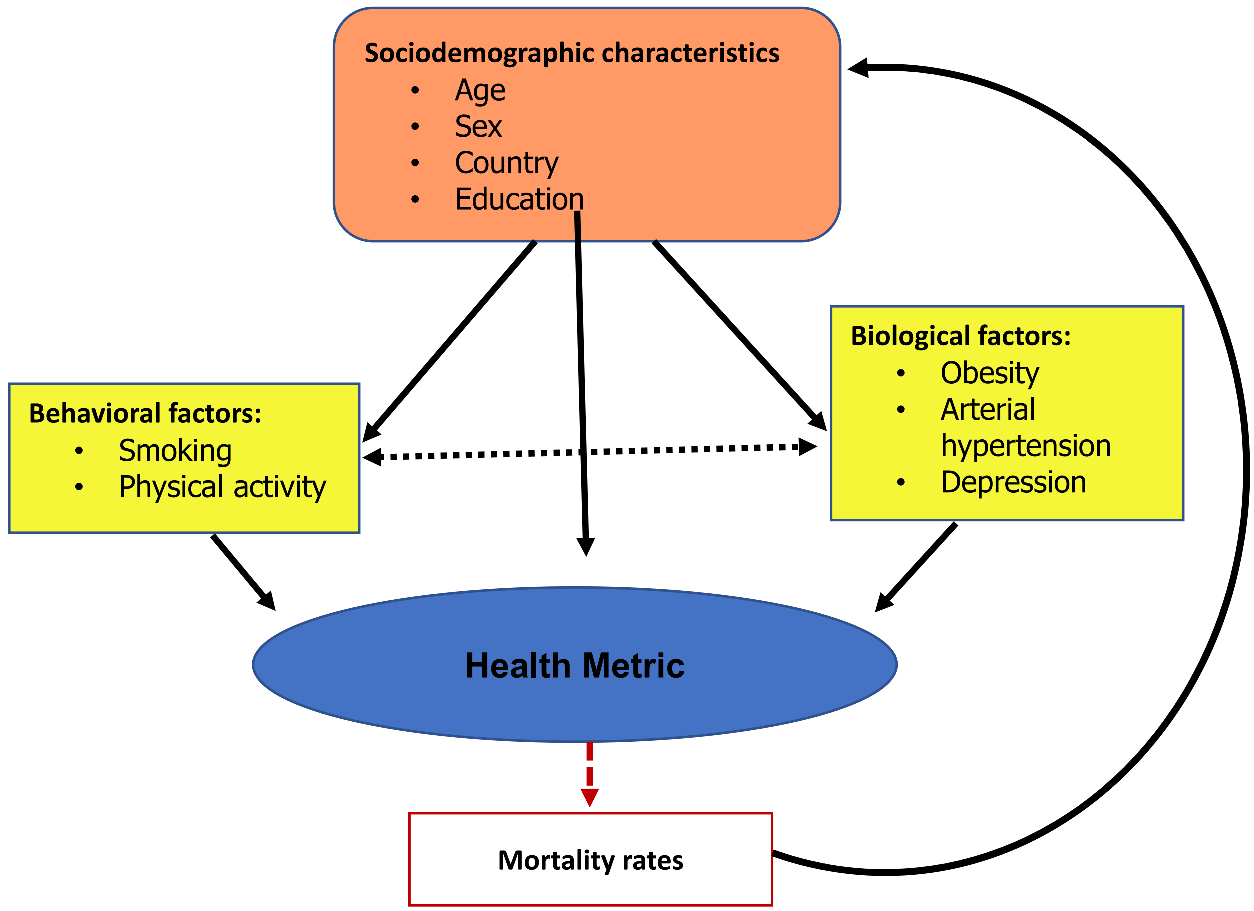
Table 1: Sample size by country and wave (in parenthesis, the retention rate, including deceases)

Country	**Wave 1 (2004)**	**Wave 2 (2007)**	**Wave 4 (2011)**	**Wave 5 (2013)**
AT	1594	1228 (72%)	5332 (56%)	4425 (76%)
BE	3827	3205 (74%)	5388 (69%)	5765 (75%)
CZ		2830	6196 (49%)	5926 (69%)
DE	3008	2614 (53%)	1623 (54%)	5719 (65%)
DK	1707	2666 (76%)	2393 (68%)	4268 (85%)
EE			6828	6064 (85%)
ES	2396	2315 (61%)	3690 (65%)	6690 (80%)
FR	3193	3021 (64%)	5954 (65%)	4588 (68%)
GR	2898	3292 (80%)		
IT	2559	3039 (71%)	3673 (68%)	4853 (73%)
NL	2979	2710 (61%)	2822 (62%)	4213 (80%)
PL		2467	1880 (67%)	
SE	3053	2802 (68%)	2122 (60%)	4713 (72%)
SI			2756	3000 (73%)
Total	27214	32189 (68%)	50657 (63%)	60224 (71%)

3.1.2 Framework

The framework of ATHLOS-Mic is schematized in Figure 1. Using sociodemographic characteristics and a set of behavioral and biological factors, the newly developed health module uses parameters from statistical models to project the health metric of cohorts born before 1961 for a selection of European countries for the horizon 2060[2]. The value of the health metric is also used to modulate the probability of survival. The module is thus dynamically implemented, as it may impact the projection's outcome for other dimensions.

Figure 1: Framework of ATHLOS-Mic's health module



Although the health may depend on a large set of determinants, the module needs to restrict them to most important ones, among those for which empirical data allow to measure their effect with consistent statistical models. Sociodemographic characteristics that are used in the health module are those already included in CEPAM-Mic:

[2] This restriction in terms of cohorts and time span is due to data limitations.

- **Age**;
- **Sex**;
- **Country of residence**;
- **Education**, which is divided in three broad categories based on ISCED classification either:
  - Low: Lower secondary or less (ISCED 1 and 2);
  - Medium: Upper secondary completed (ISCED 3);
  - High: Postsecondary (ISCED 4+).

In addition to these sociodemographic characteristics, the health module adds dimensions related to behaviors and biological factors, which need to be simulated through the life of individuals. The choice of risk factors relies on both empirical studies proving their impact on health and availability of data, since, as stated above, SHARE-HD has some limitations. These behavioral factors are:

- **Smoking status**, which is a binary variable indicating if the individual is a current smoker or not (*current_smoking* from SHARE-HD);
- **Physical activity**, which is binary variable indicating if the individual did vigorous physical activity in the last two weeks (*vig_pa* from SHARE-HD*).*

Those associated to biological factors are:

- **Obesity status**, which is a binary variable derived from the Body-Mass Index, itself derived from self-declared weight and height. The individual is considered as obese when the BMI value is equal to or above $30Kg/m^2$ (*obesity* from SHARE-HD);
- **Arterial hypertension**, which is a binary variable picked directly from SHARE-HD (*ah* from SHARE-HD).
- **Depression status**, which is a binary variable indicating if the individual suffers from depression at the moment of the survey (*depression* from SHARE-HD);

We excluded from the module the variable on the consummation of alcohol provided by SHARE-HD, because a previous study (Caballero et al. 2017) as well as preliminary analysis showed that it is positively associated with the health metric. Indeed, past studies proved that the relationship between alcohol consumption and mortality has a J-shape (Ferreira & Weems 2008). Since the variable in SHARE-HD can hardly distinguish alcoholics from moderate drinkers, it misses to capture the bad effect of alcoholism on health. Moreover, there are some evidences suggesting that people in bad health tend to reduce their alcohol consummation, thus reversing the causal effect (Holdsworth et al. 2016).
It may takes many years after quitting smoking before observing same morbidity risks as those who never smoked (U.S. Department of Health and Human Services 2004), and consequently, it would have been preferable to distinguish past smokers from those who never smoked. We however discarded this option, since the proportion of missing values in SHARE-HD for the variable *smoking* that distinguishes current smokers, past smokers, and those who never smoked is too high to insure robust statistical analysis (36% for the 4 waves). We thus used a binary variable, for which the proportion of missing values is acceptable (3%).

3.1.3 Methods

ATHLOS-Mic consists into 5 additional steps to CEPAM-Mic:

i. Imputing initial health metric and risk factors to the base population
ii. Modeling changes in sociodemographic characteristics
iii. Modeling changes in behaviors and biological factors
iv. Modeling the change in the health metric
v. Implementing the impact of the health metric on mortality

i. Imputing initial health metric and risk factors to the base population

The first step is set initial values for the health metric and risk factors. Risk factors are first imputed together to the base population of CEPAM-Mic, which already has a large set of sociodemographic characteristics. Polytomous logistic regressions from the MICE package in R (van Buuren & Groothuis-Oudshoorn 2011) are used for this purpose, using the last observation of every unique individuals of SHARE-HD (wave 2, 4 and 5). This method performs multiple simultaneous imputations based on the observed values of selected covariates, thus allowing to take the correlation among imputed variables into the account. Second, parameters from a linear regression modeling the logit of health metric by sociodemographic characteristics and risk factors are used to impute an initial value to the health metric. At the end, for every set of covariates with a significant number of individuals, the average imputed value in the base population corresponds approximatively to the one of SHARE-HD with the same set of covariates. However, because there are some differences between the base population and SHARE-HD in the composition of the population by age, sex, country, and education, small mismatches in average values at aggregated levels are possible.

ii. Modeling changes in sociodemographic characteristics

CEPAM-Mic already has core modules to perform a multistate and multiregional population projection projecting the population by age, sex, education, and country of residence. An exhaustive description of those modules can be found in other papers (Bélanger et al. 2019; Marois et al. 2019). Because the health module is only applied to the population born before 1961, the fertility module and its assumptions are irrelevant. The same way, the highest level of education is already reach at the initial year of the projection for cohorts born before 1961, meaning that any change in the education module would not affect the outcome of the health module. Thus, only the mortality and the migration modules modulate the population composition of the health module.
For the mortality, CEPAM-Mic uses as baseline mortality rates by age, sex and educational attainment are taken from Lutz et al. (2018). Future trends for these rates were determined by a panel of experts (Caselli et al. 2014). The trend in increasing life expectancy is thus assumed to continue, though at different pace by country, gender, and educational attainment. For the cohort born before 1961, the value of these rates is modulated by the health metric (step 5).
International and domestic migration assumptions are based on recent trends provided by Eurostat for the period 2013-2016. The number of international immigrants is assumed to remain constant to average observed during the period 2013-2016 (Eurostat 2018), which is about 10M for a 5 years period, while domestic migration gives an advantage to some Western Europe countries such as Germany. Since migration

rates follow the Rogers-Castro schedule (Rogers & Castro 1981), the impact of migration modules only slightly affect health outcomes. Indeed, migration generally occur between the ages of 20 to 34, whom will never reach the age of 75 during the time span of the projection.

iii. Modeling changes in behaviors and biological factors

The initial values set to individuals of the base population for behaviors and biological factors may evolve during the projection. For all of them, using the SHARE-HD described below, an autoregressive distributed lag model with duration predicting the value of factor F at time *t* is used to estimate parameters for the value of factor F at time *t-a* and a set of *i* covariates X at time *t-a*, being other risk factors and sociodemographic characteristics at time *t-a*. The equation is the following:

$$logit(F_t) = \beta_0 + \beta_1(a-1) + \beta_2 F_{t-a} + \beta_i X_{i,t-a} \quad \text{Eq.1}$$

The symbol *a* being the number of years between two observations, $\beta_1(a-1)$ is introduced to control for the varying length between years of interview, assuming linear distribution over time. When the duration is 1 year, $\beta_0 + \beta_2$ can be interpreted as being the net probability of still having a factor F for individuals who already had it 1 year before. Preliminary models also introduced interaction terms between F_{t-a} and X_{it-a} in order to test if covariates had the same effect for those who had the risk factors at time t-a and those who hadn't. Since most interaction parameters were not significant, we didn't retain these models. Models are estimated using generalized estimating equations (GEE) (Liang & Zeger 1986), which take into account correlation between outcomes, because more than one observation may be included in the database for an individual (i.e., change between wave 1 and 2 and change between waves 4 and 5).

Table 2 presents parameters for the five risk factors. First, results show a strong interrelation between risk factors. For instance, the odd of doing physical activity at time t is strongly decreased if the individual at time t-a was a smoker (-0.261), was obese (-0.333), and was depressed (-0.399). The same way, individuals have more chance to keep being depressed at time t if there were smoker at time t-a (0.197) and obese (0.125), but have less chance to be in depression if they do physical activity at time t-a (-0.234). The only risk factor that looks standing by itself is smoking, for which no parameter for other risk factors are significant.

If we take a look at the parameter for the lag variable combined with the intercept and age=65, we can derived the annual net probability of change in the risk factors for standardized profile of an individual aged 65 at time t-1 for which all other values for covariates are set to 0 (thus, living in Germany). For smoking, these parameters give a probability of 77.8%[3], which means that a 65 years old individual who smoked at time t-1 has 77.8% chance of still smoking at time t, when he'll turn 66 (all other thing being equal), and conversely, the probability of quitting smoking is 100%-77.8%=22.2%. When removing from the equation the parameter for smoker at time t-1, the resulting probability is 4.6%[4], which represents the probability to be a smoker at time t for a 65 years old individual at time t-1 who didn't smoke (though we can assume that most of them were past smokers). Table 3 presents the net transition rate for all risk factors in regards with the status at year t-1

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[3] exp(1.031+4.288+65*-0.092+65^2*4.549E-04)/(1+exp(1.031+4.288+65*-0.092+65^2*4.549E-04)) = 77.8%

[4] exp(1.031+65*-0.092+65^2*4.549E-04)/(1+exp(1.031+65*-0.092+65^2*4.549E-04)) = 4.6%

For some risk factors, the transition is quite high. The transition from a depressive status to a no depressive status reach 66.2%, but only 8.8% of non-depressive people will be in depression one year later, which shows that depression is a status that is likely to switch several times over life. For physical activity, the transition rate for those who do not do physical is quite high, 62.1%, but as a reminder, this rate, derived from regression parameters, corresponds to a very specific profile, being those without any other risk factors. For smoking and obesity, very few change status in one year: only 6.3% of non-obese people become obese, and as stated before, 4.6% of non-smoke become smokers.

As stated before, this modeling is not applied for the variable education, since the transition for education is already implemented in prior version of the microsimulation model and the variable is very stable for elderly. However, the education has a considerable influence on other risk factors. Having a low level of education increases severely the chance to be depression (0.491) and obese (0.692), while reducing the chance to do physical activity (-0.244) and increasing arterial hypertension (0.313). Parameters for education are however not significant for the smoking model, meaning the probability to stop smoking is the same for high or low educated elderly (which doesn't imply that the probability to start smoking at younger age is not influenced by education).

The figure 2 presents the age pattern for the five risk factors, net effect from other covariates. A declining trend with age is observed for smoking, obesity, and physical activity, meaning that older people have more chance to stop smoking, stop being obese, and less likely to start doing physical activities. Depression increases exponentially with age, in particular after the age of 75. The arterial hypertension is on its side at its highest in the mid-seventies, and start declining afterward.

Figure 2: Age pattern for risk factors

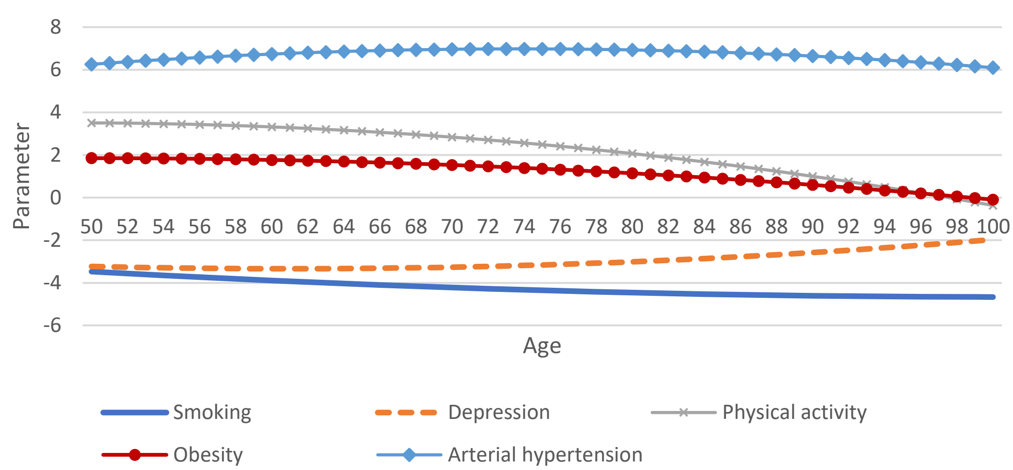


Table 2: Logit regression parameters for risk factors

Covariate (t-1)	Model for smoking (t)		Model for depression (t)		Model for physical activity (t)		Model for obesity (t)		Model for arterial hypertension (t)	
	Parameter	p-value	Parameter	p-value	Parameter	p-value	Parameter	p-value	Parameter	p-value
Intercept	1.031		0.987		-2.622	**	-4.371	**	-8.435	***
Age	-0.092		-0.110	***	0.144	***	0.075	*	0.189	***
Age*Age	4.549E-04		8.985E-04	***	-1.475E-03	***	-7.605E-04	**	-1.281E-03	***
Sex=F	-0.101		0.491	***	-0.242	***	-0.003		0.012	
Education (ref=High)										
Med	0.094		0.235	***	-0.160	**	0.358	***	0.182	**
Low	0.007		0.493	***	-0.244	***	0.692	***	0.313	***
Current smoker	4.288	***	0.197	**	-0.261	***	-0.068		-0.041	
Depressed	-0.040		1.665	***	-0.399	***	0.028		0.052	
Does physical activity	-0.058		-0.234	***	1.267	***	-0.124	*	-0.082	*
Obese	-0.033		0.125	*	-0.333	***	3.853	***	0.513	***
Has arterial hypertension	-0.005		0.110	**	-0.140	**	0.345	***	2.625	***
Country of residence (ref=DE)										
AT	-0.019		-0.232	**	-0.113		-0.157		-0.171	*
BE	-0.079		0.050		-0.490	***	-0.311	**	-0.352	***
CZ	0.330	**	-0.022		-0.434	***	-0.022		0.050	
DK	-0.236	*	-0.180	*	-0.176	**	-0.259	**	-0.294	***
EE	0.057		0.320	***	0.119		-0.005		-0.034	
ES	-0.370	**	-0.045		-0.588	***	-0.324	**	-0.334	***
FR	-0.177		0.259	**	-0.427	***	-0.411	***	-0.462	***
GR	0.362	**	-0.673	***	0.644	***	-0.463	***	-0.398	***
IT	-0.157		0.193	*	-0.586	***	-0.721	***	-0.263	**
NL	-0.180		-0.427	***	0.125		-0.309	**	-0.510	***
PL	-0.156		0.103		-0.436	***	0.021		-0.410	**
SE	-0.316	*	-0.290	**	0.074		-0.374	**	-0.223	**
SI	-0.049		0.038		0.119		0.002		0.071	
Duration	-0.006		0.082	***	-0.057	**	-0.045		0.088	***

***p<0.5; **p<0.01; ***p<0.0001**

Source: Authors' calculation using data from SHARE-HD

Table 3: Net transition rates derived from regression parameters		
Risk factor$_t$	**Risk factor$_{t-1}$=1**	**Risk factor$_{t-1}$=0**
Smoker	22.2%	4.6%
Depression	66.2%	8.8%
Physical activity	14.7%	62.1%
Obesity	24.1%	6.3%
Arterial hypertension	25.6%	17.4%

Starting with the imputed value of behavioral and biological factors in the base population (F') and using the Monte Carlo approach, those parameters are then used to predict stochastically the behavioral and biological factors F' of individuals at time t+1 throughout the projection (see equation 2).

$$F_{t+1} = \frac{\exp(\beta_0 + \beta_2 F'_t + \beta_i X_{i,t})}{1+\exp(\beta_0 + \beta_2 F'_t + \beta_i X_{i,t})}$$

$$F'_{t+1} \begin{cases} 1 & F_{t+1} < Z\sim([0,1]), \\ 0 & F_{t+1} \geq Z\sim([0,1]) \end{cases} \qquad \text{Eq.2}$$

Where $Z\sim([0,1])$ is a random number uniformly distributed between 0 and 1.

iv. Modeling the change in the health metric

The health module of the microsimulation changes through the life course the initial value of the health metric (HM) according to sociodemographic characteristics and behavioral and biological factors described in the previous section. For this purpose, we first built a linear regression model on the difference between the logit of the health metric over a year, as expressed by equation 3.

$$\frac{logit\left(\frac{HM_t}{100}\right) - logit\left(\frac{HM_{t-a}}{100}\right)}{a} =$$

$$\beta_0 + \beta_1(HM_{t-a}/100) + \beta_2(HM_{t-a}/100)^2 + \beta_3(HM_{t-a}/100)^3 + \beta_i X_{i,t-a} \qquad \text{Eq.3}$$

We used the logit form of the HM (divided by 100) in order to avoid to predict values that go beyond the range limit of the health metric (which is from 0 to 100). β_i is a set parameters capturing the effect of covariates X at time t-a (e.g. sociodemographic characteristics and behavioral and biological factors). β_1 + β_2 + β_3 allow to take into account different pace in the change of the health metric according to the initial health status. Again, the model is estimated using generalized estimating equations (GEE). Table 4 presents parameters from this model.

Results for behavioral and biological factors are as expected, since negative parameters for smoking (-0.020), depression (-0.035), obesity (-0.033) and arterial hypertension (-0.011) indicate that those factors accelerate the decline in the health metric, while the positive parameter for physical activity (0.017) confirms that positive impact of doing sport on health. The health also tends to decline faster for people with low education (-0.059) or medium education (-0.033) compared to those with high education. Indeed, education seems to be the main determinant of change in the health metric, as its parameters are stronger than any other risk factors. Concerning the age, parameters reveal that the health tends to decline faster as people getting older, following a quadratic trend. In short, those parameters are consistent with those estimated by Caballero et al. (2017) when they assess the impact of covariates on a similar health metric built with data from the English Longitudinal Study of Ageing.

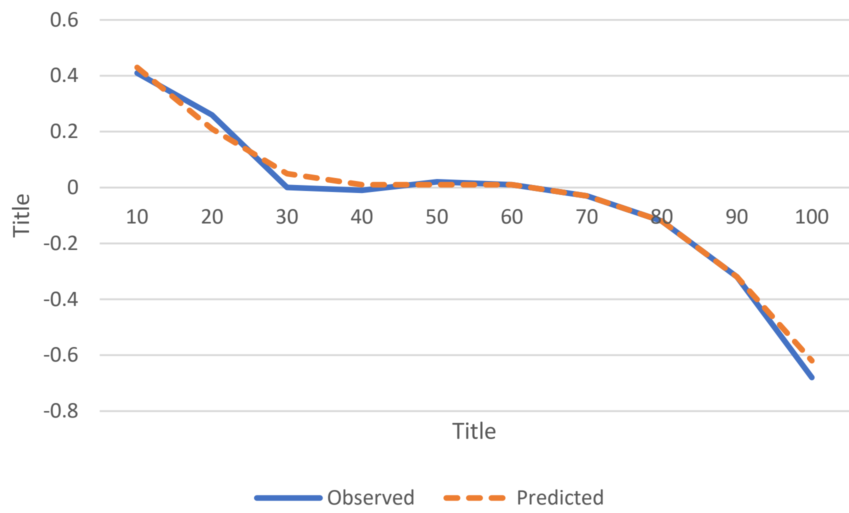
Finally, parameters for the variable country show some national variations in the pace of the decline of the health metric, all other things being equal, with a faster decline in Estonia (-0.041) and a slower one the Netherlands (0.032), in Denmark (0.036), in and in Sweden (0.037).

Using parameters from table 3 and observed values in the dataset, the Figure 3 compares predicted and observed changes in the logit of the HM over one year according to the initial value of the HI. The good fitting between the predicted curve and the observed one confirms that using the cubic form of the variable HM in equation 3 is the best fit. The shape of curves also reveals that people in good health are more likely to see their health declining, while people in medium health would not see lot change in their condition. People in bad health, on the other side, are likely to see their health improve, at least for those who survive.

Table 4: Model for change in the health metric

Covariate (t-1)	Parameter	p-value
Intercept	0.694	***
HM	-4.444	***
HM*HM	8.739	***
HM*HM*HM	-6.214	***
Age	1.202E-02	***
Age*Age	-1.301E-04	***
Sex=F	-0.015	***
Edu=Low	-0.059	***
Edu=Med	-0.033	***
Was a current smoker	-0.020	***
Depressed	-0.035	***
Did physical activity	0.017	***
Obese	-0.033	***
Has arterial hypertension	-0.011	**
Country of residence (ref=DE)		
AT	0.023	**
BE	0.005	
CZ	0.002	
DK	0.036	***
EE	-0.041	***
ES	0.009	
FR	0.004	
GR	0.013	*
IT	-0.006	
NL	0.032	***
PL	0.015	*
SE	0.037	***
SI	0.017	*
***p<0.5; **p<0.01; ***p<0.0001**		

Figure 3: Predicted and observed change in the logit of the HM between t and t+1 according to the value of the HM at time t-1



Starting from the imputed value of the health metric (HM'), parameters from equation 3 are used in ATHLOS-Mic to estimate its predicted value at time t+1, as expressed by equation 4.

$$HM'_{t+1} = 100 * \frac{\exp\left(\frac{logit(HM'_t)}{100}\right) + \beta_0 + \beta_1(HM'_t/100) + \beta_2(HM'_t/100)^2 + \beta_3(HM'_t/100)^3 + \beta_i X_{i,t-a})}{1+\exp\left(\frac{logit(HM'_t)}{100}\right) + \beta_0 + \beta_1(HM'_t/100) + \beta_2(HM'_t/100)^2 + \beta_3(HM'_t/100)^3 + \beta_i X_{i,t-a})} \quad \text{Eq. 4}$$

The predicted value of the health metric is thus deterministically calculated, but variables that are used to predict it are on their side computed stochastically.

v. Implementing the impact of the health metric on mortality

The main outcome of the health module is an individual health metric. As ATHLOS-Mic is dynamic, it is possible to use this outcome to modulate the mortality. Doing this, the health module has a direct impact on the number of survivals. In other words, any changes in assumptions on risk factors will have a direct effect on the HI, which on its side will impact the number of people who survive.
The SHARE-HD can track participants that died between two waves. Using this information, we estimated the impact of the health metric on the probability of dying (q) between t and t+a, controlling for education, age, sex and country, with equation 5.

$$logit({}_a q_t) = \beta_0 + \beta_1(a-1) + \beta_2 HM\_gr_{t-a} + \beta_i X_{i,t-a} \qquad Eq. 5$$

β_1 controls for the different duration between observations. β_i is a vector of parameters controlling the effect of age, education, sex, and country, while β_2 captures the effect of a categorical transformation of the health metric at time t-a.

Table 5: Contrasted parameters for β_2 from equation 5				
Health	**Parameter**	**Odd**	**Std.**	**% of N**
[0, 30[	1.946	6.999	0.199	4.1%
[30, 40[	1.235	3.437	0.165	7.4%
[40, 50[	0.438	1.550	0.120	16.0%
[50, 60[	0.019	1.019	0.103	23.1%
[60,	-0.457	0.633	0.079	49.3%

CEPAM-Mic already has sex-, country-, and education-specific life tables which are taken from Lutz et al. (2018). Future trends for these rates are determined after consultation of a panel of experts (Caselli et al. 2014). In ATHLOS-Mic, from equation 5, we applied on β_2 a contrast to the weighted population average in order to get parameters for all categories using the whole population as reference. Table 5 presents those contrasted parameters.

Individuals with a HM above 60 have been grouped into a single category, as well as those with a HM below 30, because few differences were observed in mortality rates within those categories. Note that about 70% of the population have an HM above 50, and that above this threshold, differences observed in mortality rates are quite low. For instance, the OR for the category [60, is 0.633, which indicates that the propensity of dying is only 34% lower than the average of those with same age, sex, country, and education. At the opposite, the parameter for the category [0, 30[corresponds to an odd ratio of 8.038 meaning that the probability of dying for those individuals is about 8 time higher than the average. However, only 4% of the population are in this category.

As expressed by equation 6, we then used those contrasted parameters (β_2) to adjust the yearly mortality rates by age, sex, country, and education that were already set in assumptions of the microsimulation. Since we used contrasted parameters on the population weighted average, the number of dead for the first year of the projection in ATHLOS-Mic is about the same as in CEPAM-Mic (which doesn't take into account the health metric), but discrepancies will appear in further years of the projection in result of changing population composition in term of health metric.

$$ {}_1q'_t = \frac{\exp\left(logit({}_1q_t\ ) + \ \beta_2 HM\_gr'_t\right)}{1+\exp\left(logit({}_1q_t\ ) + \ \beta_2 HM\_gr'_t\right)} \qquad Eq. 6 $$

Where:

${}_1q'_t$ is the age-, sex-, country, and education-specific mortality rate at time t adjusted by the health metric;

${}_1q_t$ is the age-, sex-, country, and education-specific mortality rate without adjustment;

$HM\_gr'_t$ is the predicted health index (categorized) at time t.

3.2 Definition of scenarios

We built different scenarios to test the sensitivity of risk factors on the projection outcomes and have a better understanding of dynamics in future health trajectories:

1. The Baseline scenario used all parameters from statistical models presented above. It's the scenario "business-as-usual" in which cohorts are replaced through the demographic metabolism.
2. The NoAH scenario removes the prevalence of arterial hypertension in the population;
3. The NoObe scenario removes the prevalence of obesity in the population;
4. The NoSmoke scenario removes the prevalence of smoking in the population;
5. The NoDep scenario removes the prevalence of depression in the population;
6. The NoInactive scenario supposes everyone does physical activity;
7. Since it's not possible to change education of elderly the EqEdu scenario assumes that the change in the health metric for people with low- and medium-education is the same as the change for people with high education (all other thing being equal) have the same health metric). In other words, parameters for those categories are set to 0;
8. The NoRisk scenario combines scenario 2 to 7. In other words, it removes the prevalence of all risk factors and removes the negative effect of having a low or medium education on the change in the health metric;
9. The BadHMAlive scenario assumes that people in bad health have same chance of dying than people in good health. The parameter for the probability of dying for the health metric group 70+ (HM_GR>=70) is applied to other health metric groups.

Changes in risk factors are modeled dynamically in ATHLOS-Mic. In consequence, removing a risk factor (such as what assumed in scenarios 2 to 7) not only impacts the health metric directly with the parameter associate to this risk factor in the modeling of the change in the health metric, but also indirectly, but impacting transition in other risk factors.

3.3 Results

The figure 4a first presents the projected health metric by cohort for the baseline scenario. Indeed, as cohorts get older, their health deteriorates. The generation 1956-60 starts with an average HM of 65 at the age of 55-59, which decline gradually over years to reach 22 at the age of 95-99. However, the baseline scenario also reveals that each generation will be healthier the previous one at the same age. At the age of 80-84, the generation born in 1931-1935 had an average HM of 47 (figure 4b). When they will reach these ages, the average HM of the born 1956-1960 will be 4 points higher (51). Indeed, the HM of the cohort 1956-1960 at the age of 80-84 will be similar to the one of the cohort 1936-40 at the age of 75-79, which supports Sanderson and Scherbov's (2010) idea that the conventional definition of the old-age threshold as a function of the number of years since birth should be revised, as it doesn't account for better health and increasing life expectancy. While some claim that 60 is the new 40, our projection suggests that 80 will be the new 75.
In order to have a better understanding of the improvement of health for younger cohorts revealed in figure 4, we show in figure 5 the projected risk factors by cohorts. It shows that younger cohorts tend to have better health behaviors and health conditions than older cohorts, with at a same age, lower prevalence of arterial hypertension, depression, obesity, and smoking, and higher prevalence of physical activity. Differences however are quite small. For instance, for the prevalence of arterial hypertension at the age of 80-84, it reaches 46% for the cohort 1931-1935, while it is projected to be 43% for the cohort 1956-60. The

same is observed for the prevalence of obesity, which is 28% for the cohort 1931-1935 at the age of 80-84 compared to 30% for the cohort 1956-1960 at the same age. The improvement is real and consistent over cohorts and for all age, but still not very significant.
When looking at the education, however, trends are very different. Indeed, past a certain age, the education doesn’t change over time. It becomes a persistent characteristic, and the change in the proportion in a cohort is only attributable to different mortality rates. The improvement of education attainment over cohorts is both consistent and significant. More than 70% of cohort born before 1930 have low levels of education. This proportion decreases each generation and pass below 30% for the generation 1956-1960. Since having a low level of education was the most important risk factors in the modeling of change in the health metric, we can thus conclude that the better educational attainment of younger cohorts is a major drive or their expecting better health, as it as both a strong positive effect on the health metric directly and also, on other risk factors. Indeed, education-specific health metric is not projected to change much.
In figure 6, we present the projected average health metric for cohorts born between 1916 and 1960 (a) and for the age group 80-84 (b) according to the 9 scenarios. When all risk factors are removed, the HM is improved significantly. In the baseline scenario, as the population ages, the HM passes from 57 in 2015 to 22 in 2060. In the scenario 8-NoRisk, the average HM is between 5 to 6 points higher all over the projection. For the 80-74 age group, while the HM increases from 47 to 51 in the baseline scenario between 2015 and 2040, it would reach 61 when all risk factors are removed. When looking in details, we notice that the individual scenario having the strongest effect is the one removing inequalities in education (7-EqEdu). Compared to the baseline scenario, this scenario increases the average HM by 3 to 5 points, while scenarios for other risk factors barely manage to increase the average HM by more than 1 point. On the other side, the scenario having the worst effect on the average HM in the one keeping people in bad health alive (BadHMAlive), since it keeps in the living population people with the worst health metric.

Figure 4: Projected average health metric, baseline scenario

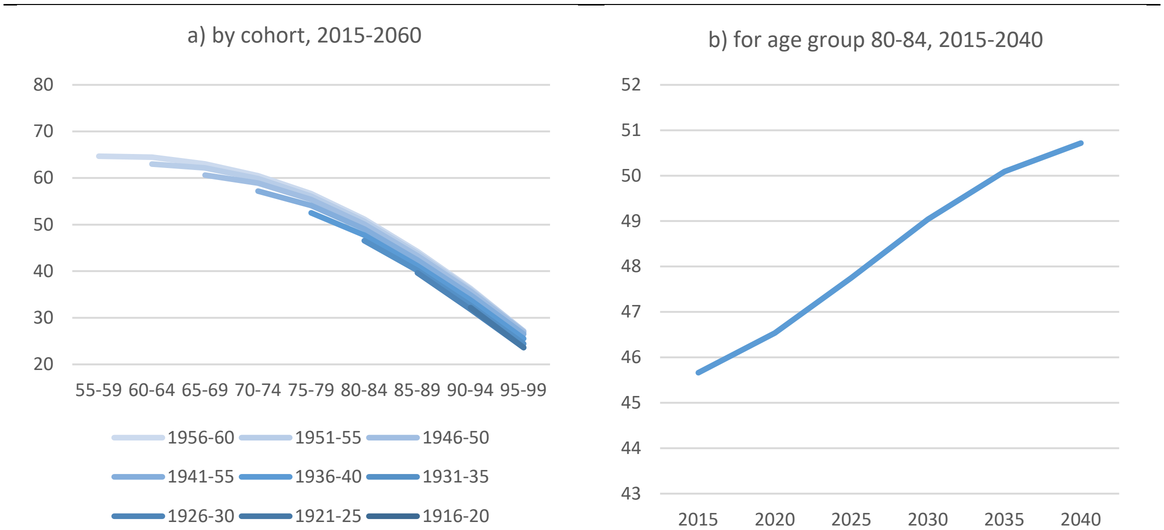


Figure 5: Projected risk factors by age and cohorts, baseline scenario, 2015-2060

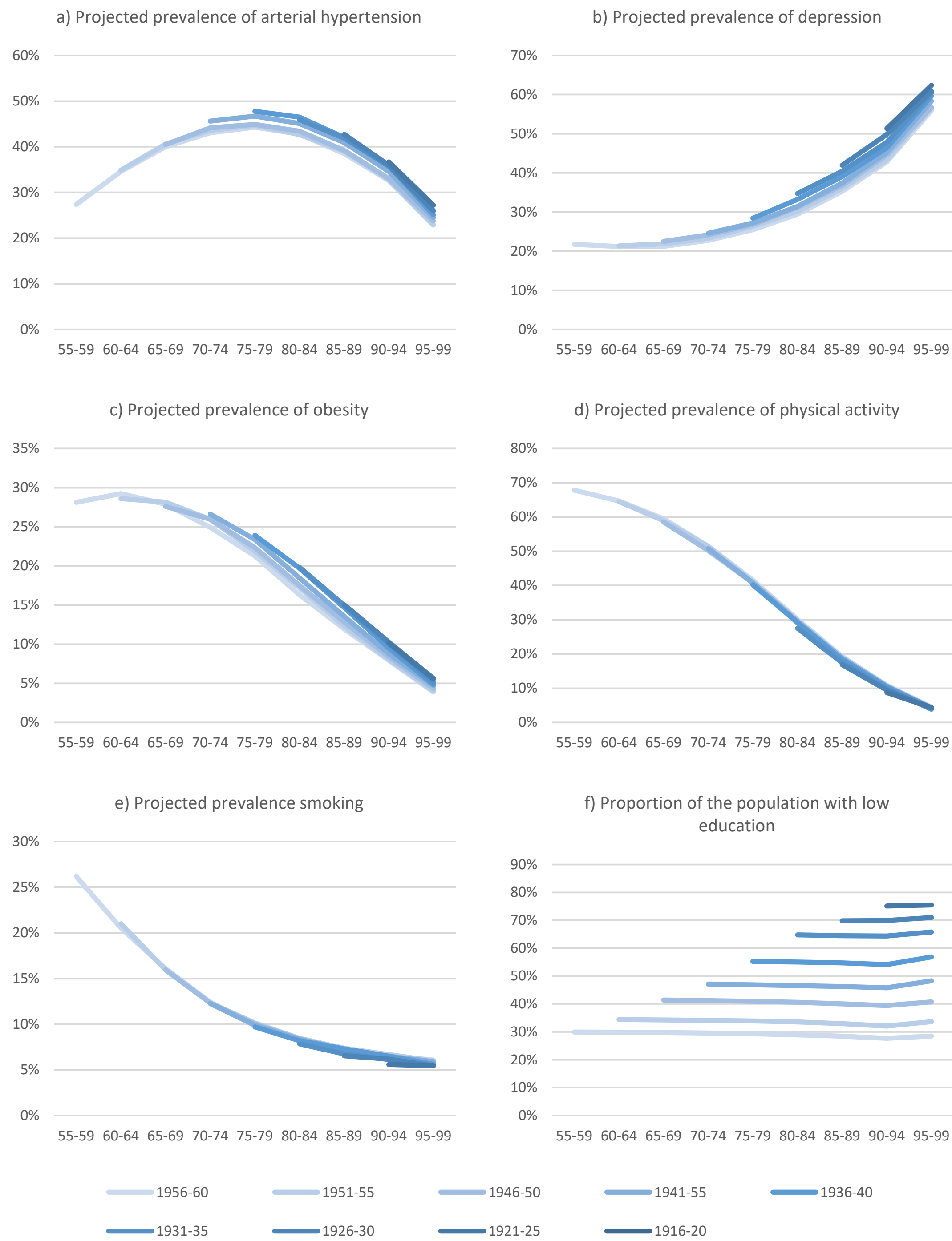
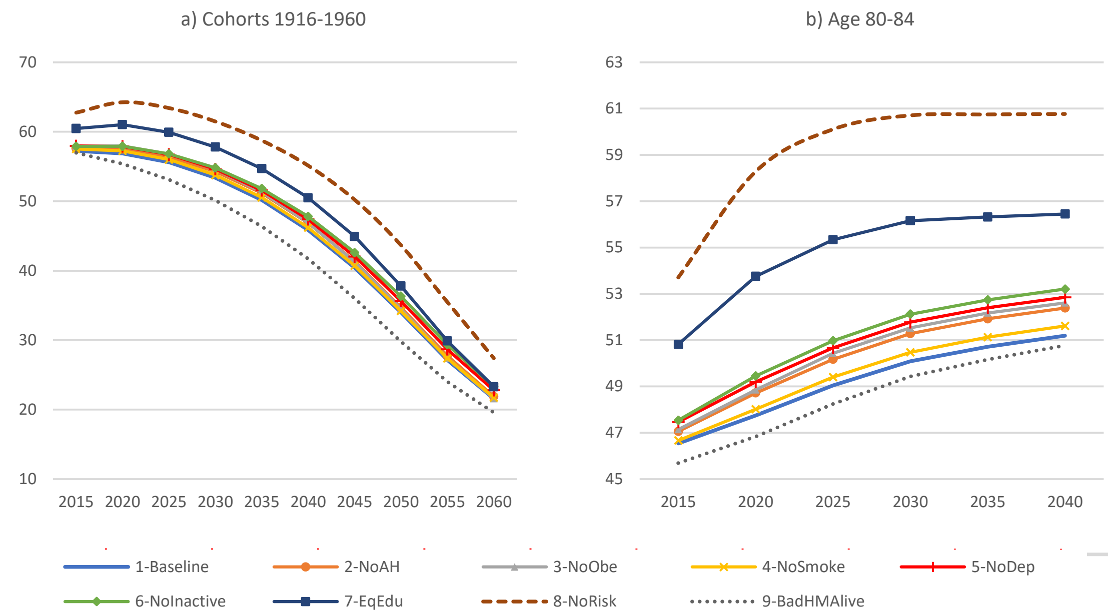


Figure 6: Projected average health metric according to different scenarios



As the health metric impacts the mortality rates, the projected number of years lived per person (NYLP) since 2015 is a relevant projection outcome to compare the health impact of scenarios. In figure 7, we compare scenarios according to the (a) projected NYLP for our projected population (cohorts born between 1916 and 1960) and (b) the difference with the baseline scenario in the projected number of years lived per person. In 2020, the NYLP for the baseline scenario is 4.6, which means that the projected population would have lived in average 4.6 years between up to 2020 (some died in between, which explains why the number is not 5). The pace of the number of years lived gradually slow down as the population get older and die. In 2050, the number of years lived per person capped at about 18. In other words, our projected population would still have 18 years to live in average in 2015. Removing all risk factors (8-NoRisk) increases by 2 years the NYLP, while the one giving the same chance of dying for people in bad health manages (BadHMAlive) to increase this number to 4, although, as we saw previously, the average health metric of the population would be lower. Aging, the individual scenario having the biggest effect is the one equalizing the change in health for low- and medium educated population (7-EqEdu), which improves the number of years lived per person by about 1.2, while scenarios removing other risk factors improve this number by less than 0.5.
As see saw in the analysis of parameters, the probability of dying starts increasing when the HM is below 60. Above this threshold, there were no much difference. We can thus use this threshold as a proxy for having a good health, and by extension, calculate the number of years lived per person in good health. The figure 8a compares the NYLP in good health from the baseline scenario with the total NYLP. In average, an individual in our base population will live about 18 years, but only 6 in good health. Indeed, past 2030, when the youngest members of the projected population reach the age of 70, almost all the additional years lived will be with a HM below 60.

Figure 7: Projected number of years live per person since 2015 according to different scenarios

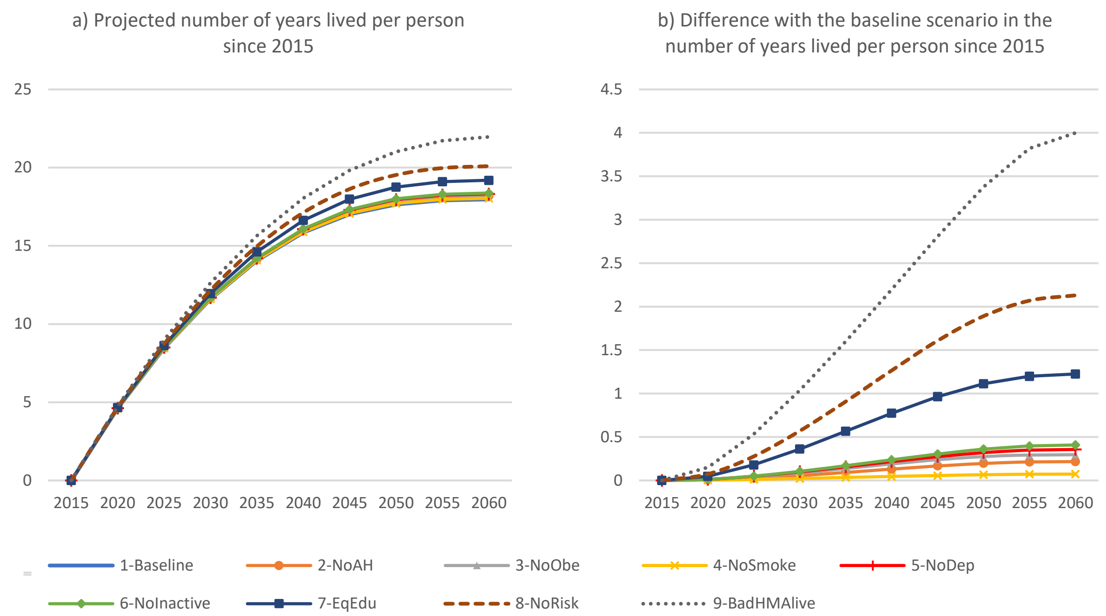


Figure 8: Projected number of years lived per person since 2015, total and in good health

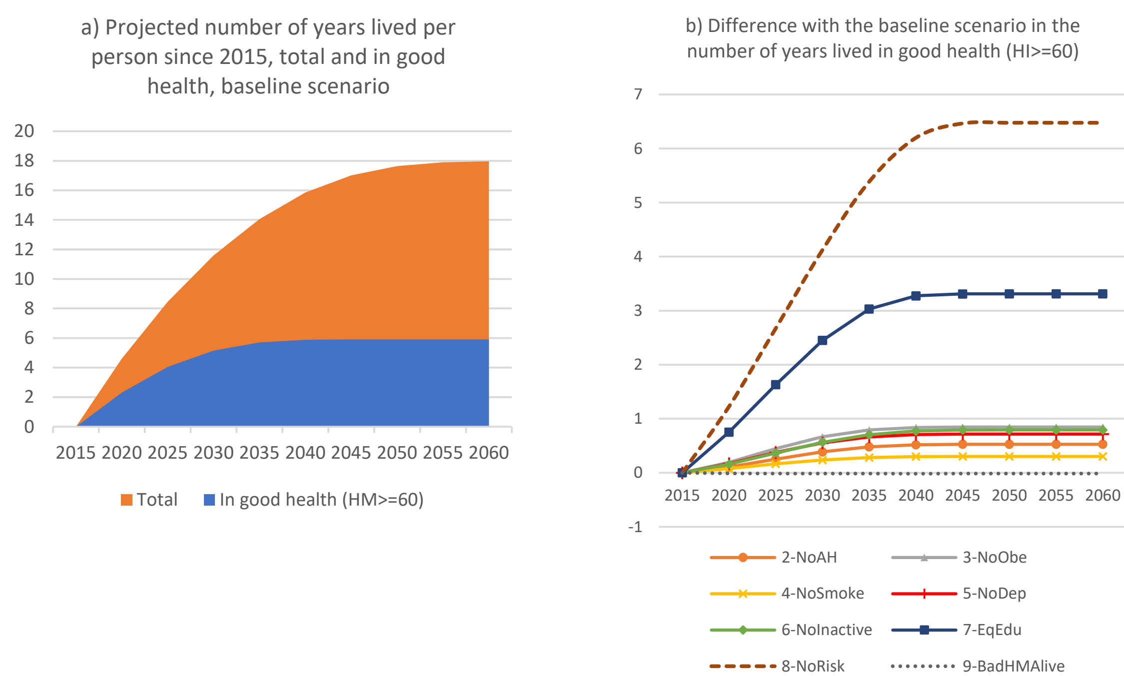
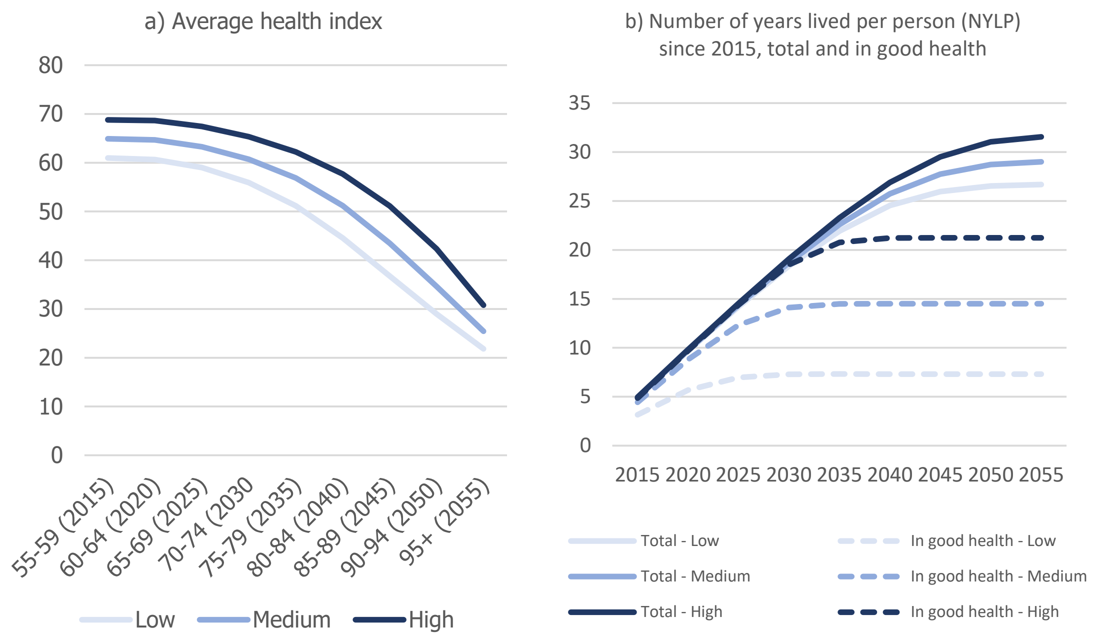


Figure 9 – Projected average health metric and number of years lived per person by education level for the cohort 1956-1960, baseline scenario



Alternative scenarios show however large variations in this indicator. Removing all risk factors (8-NoRisk) more than doubled the NYLP in good health, whcih would then exceed 12 by 2060. Again, the scenario removing inequalities in education (7-EqEdu) is the one having the largest impact, with a gain of more than 3 years compared to the baseline scenario. Other scenarios each gain between 0.4 to 1 year on the NYLP in good health. The difference between the baseline scenario and other scenarios is much lower, between 0 and 1, and is particularly small for the scenario 4-NoSmoke (a gain of only 0.3 by 2060).

Since the education stands out in its impact of the health metric, and since it also plays a major role in the prevalence of other risk factors, we show in figure 9 the health trajectory by education level for the cohort 1956-1960 in order to bring out inequalities in aging healthy within a same cohort. The education gap is obvious when looking at the average health metric (Figure 9a), as people with high level of education at the beginning of the projection (at the age of 55-59), already have an advantage of almost 10 points compared to people with low education (69 vs 61). This advantage is about constant throughout the projection, as the cohort get older. In 2050, at the age of 90-94, the gap is even risen to 13 points (42 vs 29). Indeed, the average health metric of someone with high level of education at the age of 80-84 will be about the same as someone with a low level of education at the age of 70-74 (58 vs 56).

The advantage of having a high level of education on aging healthy is also obvious when looking at the number of years lived per person (Figure 9b). At the age of 55-59, the cohort of 1956-1960 might expect to live another 32 years for those with a high level of education, which is 5 years more than those with a low level of education. Furthermore, the gap is bigger for the NYLP in good health (with a HI>=60), which reaches 21 years for people with a high level of education compare to only 7 years for people with a low level of education. In other words at the age of 55-60, people with a high level of education will live almost 70% of their remaining life in good health, while this proportion would reach only 27% for those with a low level of education. Education thus not only matters for the number of years lived, but also much more for the quality of life of these years.

4. Discussion and conclusion

This report presented an innovative methodological framework for projecting the health of individuals with a set of risk factors using a microsimulation model. The model developed, called ATHLOS-Mic, simulates the lives of individuals using statistical models that explicitly take into account interactions between the different dimensions, either biological and behavioral risk factors, socioeconomic characteristics, a health metric, and mortality.

The incorporation of a health metric and risk factors improve projections from different ways. First, there are relevant outputs. Indeed, as traditional demographic projections can project the age of individuals, they don't say anything about their health condition. This is even more important as we know that the correlation between age and health hides a lot of heterogeneity among the population and changes over time (Sanderson & Scherbov 2010; Wagner et al. 2016). Our baseline scenario revealed that each generation will be healthier than the previous one at the same age, which supports the need to reassess the definition of old-age threshold (Sanderson & Scherbov 2010).

Second, implementing additional dimensions allows to take into account more sources of heterogeneity within groups, which thus improves the overall quality of the projection outcomes. Traditional demographic projection methods only use age and sex as determinants of mortality, while multistate models and previous microsimulation models include the education (Lutz & KC 2011; Marois et al. 2019). In addition to this, ATHLOS-Mic allows the health status to vary within a same age-sex-education group, which thus leads to different probabilities of dying.

Third, ATHLOS-Mic allows to build a large set of alternative scenarios that go beyond variations around a baseline scenario, such as what is usually done by statistical agencies with "high" and "low" assumptions of fertility, mortality and migration. In this paper, we built 8 policy-oriented scenarios around interactions between risk factors, health metric and mortality. Those scenarios allow to have a better understanding on the dynamic of aging healthy, to estimate future inequalities in health, and to help policy makers to choose appropriate actions to improve health conditions.

Our scenarios analysis revealed that the education stands out among other risk factors as the main source of inequality in health. The scenario removing the effect of having a low level of education on the health metric is the one having the largest effect on both the projected average health metric (increased by 3 to 5 points compared to the baseline scenario), the average number of years lived per person (increased by 1.2 compared to the baseline scenario), and the average number of years lived in good health (increased by more than 3). Mathematically, this big effect is explained by two factors. First, the parameter associated to a low level of education (and to a less extend to medium education) in the regression modeling the health metric is much more important than those for other risk factors. Second, the share of those with low levels of education in the population (about 45% in 2015) is large and in consequence, a lot of people are affected by a change in the effect of this component. From a policy perspective, this result highlights how investments in education matter to improve the health of the population.

It may also look surprising that the scenario removing inequalities in education from ATHLOS-Mic has a more positive impact than the scenario changing the prevalence of other widely known risk factors such as smoking or physical activity. We might suspect a possible measurement issue that biases their statistical association with health. In reminder, we used a longitudinal survey with only few years between waves. Thus, statistical models consider the effect of smoking or physical activity on the degradation of health during a short period only. Since people that experienced deterioration of health are probably more likely to stop smoking or to stop doing sports, the causal relation between health and smoking could be reversed. Indeed, using a similar

health metric Caballero et al. (2017) found out that former smokers have worse health than current smokers. These authors observed the same for the alcohol consumption, as people in bad health are already more likely to not drink. In ATHLOS-Mic, we modelled the change in the health metric, but the period of observation (2 years in average) is probably too short to completely remove these reversed causal relationships and to measure properly the long-term effect of bad life habits on the health deterioration.
We might also suspect the same type of issue for obesity, as people who are in bad conditions might lose a lot of weight and have a very low body mass index (Adams et al. 2006). A multinomial variable distinguishing underweight people would thus be more appropriated to measure the net effect of obesity on the deterioration of health.
In any case, having more information on risk factors during the adult life might improve the modeling of the health metric, as the effect of bad life habits take several years to disappear. In our model, the effect of past bad life habits is probably captured by the education variable, which would partly explain its very strong effect.

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