



Masterthesis

Martina Otavova Public Health Methodology

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Faculty of Sciences School for Information Technology

Master of Statistics

Impact of tobacco control interventions on health expectancies: use of dynamic modelling for health impact assessment in Belgium

Thesis presented in fulfillment of the requirements for the degree of Master of Statistics, specialization Epidemiology &





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Abstract

Objectives: We aimed to investigate the impact of different tobacco control interventions on health expectancies, i.e. healthy life years (HLY), total life expectancy (LE), and unhealthy life years (ULY).

Methods: Data on smoking and disability from participants of the 2013 Health Interview Survey in Belgium were used to estimate smoking and disability prevalence. Disability was defined based on the Global Activity Limitation Indicator (GALI). We used a dynamic model, DYNAMO-HIA, to quantify the impacts of risk factor changes on health expectancies, comparing the "business-as-usual" scenario with multiple alternative scenarios.

Results: The "business-as-usual" scenario estimated that a cohort of 15-year-old men/women is expected to live 49.89/51.59 years (y) without disability and 14.02y/17.23y with disability. The "smoking-free population" scenario added 3.62y/2.79y in HLY and reduced ULY by 0.78y/1.81y. The "zero (re)start probabilities and all smokers quit" scenario, potentially reflecting the impact of new policies that combine smoking cessation interventions with strategies for preventing smoking initiation, yielded the largest increase in HLY (2.98y/2.35y) and the greatest reduction in ULY (-0.76y/-1.63y). Every simulated scenario reported an increase in HLY and a decrease in ULY when compared to the reference scenario, only the effect size and the timing varied.

Conclusion: This study suggests that smoking yields major losses in terms of HLY and LE in Belgium. The comparisons of alternative scenarios with the "business-as-usual" scenario indicate that implementation of new anti-smoking strategies or stricter enforcement of already existing policy/intervention methods would potentially gain more HLY and reduce ULY.

Keywords: disability, healthy life years, smoking, DYNAMO-HIA, unhealthy life years, disability-free life expectancy, smoking intervention

1 Introduction

Smoking is one of the leading risk factors for preventable and premature mortality, causing nearly 7.2 million deaths per year worldwide [1]. Association between smoking and disability has been reported as tobacco use contributes to the pathogenesis of several chronic diseases, such as cancer, cardiovascular diseases, and chronic respiratory diseases, and worsens already existing medical conditions [2–5]. The most harmful impact of tobacco consumption is mostly seen in late adulthood, but children, adolescents and young adults may also be afflicted in terms of quality of life or its length, i.e. tobacco use and second hand smoke exposure reduces the disability-free life expectancies [3].

Health expectancies are summary measures of population health combining morbidity and mortality into a single indicator. Healthy life years, also known as disability-free life expectancy, is an indicator based on limitations in daily activities and measures how many years an individual at a particular age is expected to live without disability [6]. Due to the global phenomenon of population aging, increasing the healthy life years became a main objective of many European policies. For example, the European Innovation Partnership on Active and Healthy Aging aims to increase the average number of healthy life years in the EU by 2 years by the year 2020 [7]. At the Belgian level, an improvement of health expectancy and quality-of-life are two main goals formulated in the Belgian health system performance assessment report 2015 (HSPA) [8].

Negative health impacts of tobacco consumption are widely known, yet about 23% of Belgian population aged 15 years or older still smoked in 2013 [9]. In 2004, Belgium signed the WHO Framework Convention on Tobacco Control (WHO FCTC), a treaty reassuring the right of an individual to the highest standard of health [10]. Since then many anti-smoking policies were implemented and a slight but continuous reduction in the smoking prevalence has been observed (2004: 27.7%; 2008: 24.5%; 2013: 23%) [11]. Belgian government banned smoking in the public and work places, restaurants, bars and schools. Recently, the Walloon government approved a ban on smoking in cars in the presence of minors (children until 16 years of age). Smoking policies enforced by the WHO FCTC also include bans on tobacco advertising, promotion, and sponsorship, and changes in tobacco taxation policy. Currently existing smoking interventions in Belgium further include smoking prevention and smoking cessation programs promoted by the health-care facilities and

educational institutions. Smoking cessation support on individual level is available at hospitals, health clinics and other primary care facilities. There is also a toll-free quit line available for discussing smoking cessation issues and the cost of smoking cessation treatments is partially covered by the national/federal health insurance or the national health service [10, 12].

In spite of active implementation of various anti-smoking laws and interventions, Belgium dropped from 13th (2013) to 17th place out of 30 European countries on the Tobacco Control Scale 2016 (TCS) in 2016 [13]. According to the TCS, a questionnaire designed by tobacco control experts to measure the implementation of smoking policies/interventions systematically at country level, Belgium failed in implementing a comprehensive anti-tobacco plan [14]. To become a leader in the fight against smoking, Belgium government is expected to increase the budget for tobacco prevention campaigns and implement more effective anti-tobacco measures.

In this study, we investigate the impact of various alternative tobacco control interventions on health expectancies. The tobacco control interventions are introduced as "what-if" scenarios or policy/intervention scenarios, i.e. what if every smoker quits smoking or a new nationwide policy is implemented raising the legal age to buy tobacco products from 16 to 18? We use a software, DYNAMO-HIA 2.0.7, which allows us to quantitatively compare the alternative scenarios with the "business-as-usual" scenario. To measure the impact on disability-free life expectancies and overall life expectancies, the software quantifies the effects of risk factor changes that are assumed to be initiated by newly enforced interventions and policies. We use the tool to calculate the reduction in HLY due to smoking and the potential gains in HLY due to implementing new policies. In addition, we simulate the effects of various scenarios on the future prevalence of smokers in Belgium.

2 Methods and Data

2.1 Health Impact Assessment

Health impact assessment (HIA) is a combination of methods, procedures, and tools for assessing the potential effect of a policy, project, or an intervention on the health of a population [15]. Generally, HIA aims to predict the future consequences of various policies and to support decision makers in choosing among multiple choices [16]. Although various softwares were used for the HIA in the past, DYNAMO-HIA is the only quantification tool exclusively developed for the purposes of health impact assessment [17].

2.2 Dynamo-HIA Software

In 2007, a research consortium was established for the purpose of designing a publicly available generic software that would quantify the impact of risk factor changes on overall population health due to interventions or policies. [18].

The strategy implemented by the consortium was to study and learn from the existing models instead of inventing a fully new method. For that purpose a literature search was conducted to find models sufficiently generic that allow for modeling of multiple diseases or arbitrary risk factors and take into account the standard causal pathway. A search based on the two criteria identified six models: (1)ARMADA (Age-Related Morbidity and Death Analysis); (2) GBD (Global burden of Disease); (3) POHEM (Population Health Modeling); (4) PREVENT; (5) MSLT (Proportional Multi-State Life Table); and (6) RIVM CDM (Chronic Disease Model). Their further evaluation was based on three sets of criteria required from a standard tool for HIA, recognized by HIA practitioners and modeling experts. The first set of technical criteria required that the tool models changes in an arbitrary risk factor exposure over time in a real-life population. The second set of usability criteria required that the model uses a modest data input but generates a rich model output; and the third set of criteria required that the model is publicly accessible and does not require the user to possess a profound technical knowledge. Comparison of the six models against these criteria is given in Appendix, Table A1. It shows that none of the models fulfills all the criteria and can be qualified as a standard tool for HIA. Their characteristics most suitable for an HIA tool, however, laid a foundation for DYNAMO-HIA software [18].

The work of the consortium resulted in designing a Markov-type model, DYNAMO-HIA (Dynamic Modeling for Health Impact Assessment). This model is based on a multi-state model (MSM) and satisfies all the criteria within the HIA framework [17, 18]. In a comparison to existing models, DYNAMO-HIA offered a compromise between being sufficiently technically accurate and being widely used. For instance, models, such as POHEM, RIVM-CDM, and ARMADA are more complex but are not publicly available, and require more profound knowledge of programing. Other models, such as MSLT or GBD are more accessible but lack a dynamic projection and modeling of explicit risk factor states.

DYNAMO-HIA enables to compare the health impact of different policy scenarios over time, by comparing an alternative scenario with the "business-as-usual" scenario [19]. Policies can be modeled in two ways: (1) by specifying the risk factor prevalence that is assumed to be reached with an intervention; or (2) by altering the transition probabilities between the risk factor states [17].

DYNAMO-HIA is partial micro-simulation model that combines a stochastic micro-simulation to generate the risk factor histories with a deterministic method for the disease-life table to calculate disease, disability or survival probabilities. This approach enables users to simulate the risk factor exposure in detail while avoiding the need for a large number of simulated individuals due to the rareness of chronic disease or the death event [21].

The modeling takes place in the following steps. Initially, a baseline population of individuals is generated, based on the risk factor prevalence data provided by the user. Consequently, the software applies the simulation module to simulate the risk factor histories of each individual over time under the "business-as-usual" and policy scenarios. In one-year time steps, four characteristics are updated: age, risk factor state, survival probability, and disease probability (if simulated). To run a risk factor Markov model, the transition probabilities between the risk factor states are needed. DYNAMO-HIA applies an epidemiological model that can estimate the nett transition probabilities from risk factor prevalence, relative risk (RR) for death, and baseline all-cause mortality assuming the age specific risk factor exposure does not change over time [20]. After the simulation is run, in a post-processing step, the simulation results are scaled up toward the real-life population and disability-free life expectancy and total life expectancy are calculated [18].

Validity of the DYNAMO-HIA Model

Plausibility, formal validity and predictive validity are three criteria used to assess the validity of models in HIA [21]. Plausibility refers to the degree to which a modeling tool is understandable, applicable, and plausible by users. DYNAMO-HIA is restricted to the epidemiological causal pathway where a decrease in a risk factor exposure results in decreased incidence and prevalence of disease or disability, disease-related/disability-related mortality and in turn to an improvement of population health. Formal validity evaluates whether the correct methods are applied in a correct way. DYNAMO-HIA is based on epidemiological evidence and demographic modeling practice, using incidence, prevalence and excess mortality to model an impact of an arbitrary risk factor on health expectancies. Predictive validity refers to how accurate the prediction is when confirmed by facts. In HIA, however, the time lag between the implementation of a new policy and its impact on population health may be decades long making any evaluation of HIA prediction hardly possible [17, 21].

DYNAMO HIA-1.0 vs. DYNAMO HIA-2.0

The original software, DYNAMO-HIA 1.0, did not allow the impact of the risk factor exposure on life expectancy without modeling the causally related diseases. An updated version, DYNAMO-HIA 2.0, used for the simulations presented in this paper, models the impact of the risk factor prevalence on disability-free life expectancy directly by using the overall odds ratio (OR) of disability. In this case, a hazard ratio of (other-cause) disability is calculated by combining the disability prevalence and overall odds ratio (OR) of disability. This modeling approach requires the following age and gender specific input data: (1) country-specific data on population structure, observed mortality rates and projection of newborns; (2) country-specific data on disability prevalence; (3) the risk factor exposure in Belgium; (4) OR of disability quantifying the association between smoking and disability and RR of death quantifying the RR of smoking on total mortality.

Information on smoking exposure and disability were obtained from the Belgian Health Interview Survey 2013.

2.3 Belgian Health Interview Survey

The Belgian Health Interview Survey (BHIS) is a cross-sectional household interview survey, conducted periodically every 4 to 5 years in Belgium to collect health information from around 10,000 participants. The National Population Registry (NPR) is used as a sampling frame and participants are chosen through a multistage stratified sampling design. The detailed methodology of the survey is described elsewhere [16,22]. For our analysis, we used data from the BHIS 2013 and included only participants aged 15 years and above. To collect the health data, 8,850 households were contacted, of which 5,049 participated (57%) [23]. After excluding individuals with incomplete information on disability and smoking, our final sample had a population of 6,085 individuals. More information on the BHIS 2013 is available on: https://his.wiv-isp.be/SitePages/Home.aspx.

2.4 Global Activity Limitation Indicator and Healthy Life Years

The Global Activity Limitation Indicator (GALI) is the foundation of the main health indicator in European strategic policies, healthy life years, also known as disability-free life expectancy [24]. GALI is a single-item survey instrument that aims to identify individuals in a population who consider themselves as having longterm, health-related restrictions or limitations in their daily activities [26]. The survey participants are asked to answer the question: *"For at least the past six months,* to what extent have you been limited because of a health problem in activities people usually do?" The possible responses include three severity levels: "severely limited", "limited but not severely" and "not limited at all" [25]. Individuals are considered to be disabled, when they report themselves as severely limited or limited but not severely, as is commonly done when computing the HLY indicator [27].

Healthy life years (HLY), total life expectancy (LE) and unhealthy life years (ULY) are the summary measures of population health calculated in our study. Total life expectancy is LE with disability limitation, while ULY is the difference between HLY and total life expectancy.

In the DYNAMO-HIA software, HLY, ULY and LE are calculated either as cohort or cross-sectional health expectancies. Cohort health expectancies are calculated for a real cohort and are based on a cohort life table that calculates the LE using cohort-specific birth and mortality rates stratified by age from birth [28]. In DYNAMO-HIA, the number of years lived in a certain health state during the follow-up period by all the simulated individuals is summed up and divided by the total number of simulated people at the baseline. Cross-sectional health expectance are calculated based on Sullivan's method. Sullivan's health expectancy is a measure utilizing the mortality - the difference between the survival this year and the next year - from a period life table. To calculate this type of health expectancies for a particular year, DYNAMO-HIA uses a two-step process. First, it calculates mortality in that given year by taking the difference between the survival in the current year and the next year. Then it combines mortality with disability prevalence in that year into a period life table that is based on information from the one calendar year. Cohort and Sullivan's life expectancies are calculated for individuals between ages 0 and 95 [20].

2.5 Smoothing Smoking Prevalence of Belgium

Age and gender-specific smoking prevalence for individuals aged 15 and above was derived from the BHIS 2013 in a multi-step process using the R software, version 3.5.0. Firstly, multiple fractional polynomials were fitted separately for current, never, and former smokers to accommodate the non-linear association between the continuous age and smoking status. We used the function mfp from the mfp package. Selection of the best models was based on AIC. The fitted two degree fractional polynomial models were:

$$logit\{P(y_i=1)\} = \beta_0 + \beta_1 \cdot sex_i + \beta_2 \cdot age_i^{p_1} + \beta_3 \cdot age_i^{p_2} \tag{1}$$

Where y_i indicates the response of the i^{th} individual and $y_i \sim B(n, \pi)$; p_1 and p_2 are fractional powers. The combinations of chosen powers for the variable age are shown in Appendix, Table A2.

In the next step, the complex survey design of BHIS 2013, namely the stratification, clustering on a household level and sampling weights, was taken into account by employing the R function svydesign from the survey package. The svydesign function produced a survey design object by taking the description of the survey design and adding it to the dataset [29]. This survey design object was then used in the analysis. In the last step, the svyglm function (survey package) was applied to fit generalized linear models (based on the chosen fractional polynomial models) and simultaneously account for the survey design. The following model was fitted separately for never, current and former smokers using the svyglm function:

$$logit\{P(y_i=1)\} = \beta_0 + \beta_1 \cdot sex_i + \beta_2 \cdot age_i^{p_1} + \beta_3 \cdot age_i^{p_2}$$
(2)

Where y_i indicates the response of the i^{th} individual and $y_i \sim B(n, \pi)$; p_1 and p_2 are fractional powers shown in Appendix, Table A2. For binomial distribution, family=quasibinomial() was specified to avoid a warning about non-integer numbers of successes. For more information about the mfp and survey R packages, see citations [30, 31]. Smoking prevalence by age and sex is given in Appendix, Figure A1.

2.6 Disability Prevalence and Odds Ratios for Disability

Age and gender-specific disability prevalence and the odds ratios of disability based on the GALI instrument were derived from BHIS 2013. As described above, an object with survey design information was created by employing the svydesign function. The svyglm function was then used to fit a generalized linear model to the survey design object data. When estimating the disability prevalence within the logistic framework, disability was considered a binary outcome and age and sex were included as explanatory variables. The following model was fitted:

$$logit\{P(y_i = 1)\} = \beta_0 + \beta_1 \cdot age_i + \beta_2 \cdot sex_i$$
(3)

Where y_i indicates the response of the i^{th} individual and $y_i \sim B(n, \pi)$, specified as family=quasibinomial() in the R software.

Similar approach was used to obtain the odds ratios linking smoking status to disability. Two survey design objects were created, for men and women separately, and the following generalized linear model, with correction for continuous age and smoking status, was fitted to each of the objects:

$$logit\{P(y_i = 1)\} = \beta_0 + \beta_1 \cdot age_i + \beta_2 \cdot smoking_i$$
(4)

Where y_i indicates the probability to be disabled for the i^{th} individual and $y_i \sim B(n, \pi)$, specified as family=quasibinomial() in the R software.

The odds ratios for disability, quantifying the association between the risk factor status and disability, were assumed to be gender specific but constant across age groups. The disability prevalence and the odds ratios are given in Appendix, Figure A3 and Table A3.

2.7 Transition Probabilities

Transition probabilities of the risk factor smoking were directly derived by DYNAMO-HIA from the input data - risk factor prevalence, RR for all-cause mortality (RR for death), and baseline all-cause mortality [19]. The transition probabilities or nett transition rates are estimated such as the age specific prevalence of smoking stays stable over time, i.e. in the future, the age distribution of the risk factor smoking is assumed to be the same as the current distribution by age [20, 32]. To simulate different scenarios, these nett transition rates were further manipulated in the Rsoftware and then exported back to the DYNAMO-HIA tool. For instance, quit probabilities were increased to model the potential impact of smoking cessation interventions or (re)start probabilities were decreased to model a potential impact of interventions preventing smoking initiation.

2.8 Other Data Sources

Relative Risks for Mortality

Gender-specific relative risks of the risk factor smoking on total mortality were obtained from a study by Charafeddine et. al. [33]. The overview of RR values is given in the Appendix, Table A4.

Demographic Information

Population size and mortality rates by age and sex for the year 2016 were derived from the Belgian Statistical Office [34]. The projection of newborns between the years 2018 and 2050 was derived from the United Nations World Population Prospects [35].

2.9 Scenarios

Multiple "what-if" and policy/intervention scenarios - each characterized by either a change in (re)start or quit transition probabilities or in smoking prevalence - were simulated and compared to the "business-as-usual" scenario in terms of changes in the HLY, ULY and LE, and their projected prevalence of never, current, and former smokers. The results in this paper focus on showing the impact of different scenarios in the short and long run, i.e. HLY, ULY, and LE for the individuals at the age of 15 in 2018, 2028 and 2048 and prevalence of smoking by age in 2028 and 2048. A brief overview of the scenarios is given in Table 1.

Table 1: Overview of "what-if" scenarios and policy/interventions used in the study

	Change compared to the reference scenario	
"What-if" scenarios		
1. Smoking-free population	Population consists of never smokers only	
2. Zero (re)start probabilities	(Re)start chances equal 0%	
3. All smokers quit	Quit chances equal 100%	
A Zero (re)start probabilities and all smokers quit	(Re)start chances equal 0%	
4. Zero (rejstart probabilities and an smokers quit	Quit chances equal 100%	
5 Smoking prevalence of Sweden	Prevalence of never, current and former	
5. Shloking prevalence of Sweden	smokers in Sweden in 2016	
Policy/Intervention Scenarios		
6. No smoking initiation before age 18	Zero smoking prevalence below age 18	
7. 30% increase in quit probabilities	Quit chances are multiplied by 1.3	
8. Doubling quit probabilities	Quit chances are multiplied by 2.0	

Reference Scenario

The reference scenario is based on the current prevalence of never, current and former smokers, stratified by age and gender, and on the current transition rates between the risk factor groups. The reference or "business-as-usual" scenario is taking into account only the currently existing smoking control policies, without any additional interventions.

"What-if" Scenarios

First we simulate the "smoking-free population" scenario to quantify the full burden of smoking on the overall population health. By definition, smoking-free population consists only of never smokers.

The next three scenarios simulate possible changes in (re)start and quit behavior that would result from establishing new initiation and/or smoking cessation policies. In the "zero (re)start probabilities" scenario, all age and sex-specific (re)start chances are set to 0, i.e. no influx of new smokers occurs. In the "all smokers quit" scenario, all age and sex-specific quit chances are set to 100%, i.e. all current smokers become former smokers. The third scenario - "zero (re)start probabilities and all smokers quit" - is a combination of the two previous scenarios and quantifies the health burden of smoking in a population consisting only of former and never smokers. In all three scenarios, it was assumed that 100% of the population will be reached to quantify the maximum effect of these policies.

Lastly, the "smoking prevalence of Sweden" scenario is modeled to quantify the health burden of smoking if the smoking prevalence in Belgium matched to the one in Sweden, a country with the lowest smoking prevalence in Europe according to the Organization for Economic Co-operation and Development (OECD) [36]. The data on prevalence of smoking in Sweden from 2016 were obtained from the Public Health Agency of Sweden. The prevalence of never, current and former smokers is given in Appendix, Figure A2.

Policy/Intervention Scenarios

In the "no smoking initiation before age 18" scenario, the prevalence of smoking is manipulated, i.e. no current or former smokers occur in the age groups below 18. This scenario would quantify the impact of a nationwide policy raising the legal age to buy tobacco products from 16 to 18.

In the "30% increase in quit probabilities" scenario and "doubling quit probabilities" scenario, the impact of changes in quit behavior is investigated. The former corresponds to the lower bound of an increase in quit probabilities if the smoking quit interventions are provided by medical personnel, the latter corresponds to the odds ratio (OR) of 2.0 quantifying the effect size of smoking cessation interventions among individuals aged 18 years and over [37, 38].

In addition, a simulation study is conducted to quantify the effects of gradual increases in quit probabilities by applying multiplication factors ranging from 1 to 2 in steps of 0.1 to the quit probabilities.

3 Results

3.1 Effect of Scenarios on Smoking Prevalence

Prevalence of never, current and former smokers by age for years 2028 and 2048 for all scenarios is shown separately for the male and female populations in Figure 1 and Figure 2. Changes in prevalence of smoking discussed below focus on the shortand long-term effects of alternative scenarios by 2028 and 2048.

In the "business-as-usual scenario", the prevalence of current smokers relates to the current situation, reflecting the smoking policies and interventions already in place. In the "smoking-free-population" scenario, the prevalence of current smokers is by definition 100% during the entire simulation period. The "zero (re)start probabilities" scenario causes a reduction in the prevalence of current smokers as compared to the reference scenario. By 2028, this reduction is mainly observed among the younger ages and is mirrored by an increase in never smokers. Increased projection time allows the effect of this scenario to become observable among the middle and higher ages as the adolescents grow older and reach middle and late adulthood. The "all smokers quit" scenario causes an immediate reduction in the prevalence of current smokers, mirrored by an increase in the prevalence of former smokers when compared to the "business-as-usual scenario". This reduction in prevalence of current smokers is greater in the first years after the intervention and becomes stable after 30 years. By definition, this intervention does not affect the prevalence of never smokers. The same trend is observed in the short and long run.

The "no smoking initiation before age 18" scenario reduces the prevalence of smokers among adolescents slightly, keeping this trend constant over time. The "30% increase in quit probabilities" scenario causes initially a small reduction in the prevalence of smokers at all ages but with time, larger reduction is observed in late adulthood. Similar pattern but with more strength is observed for the "doubling quit probabilities" scenario.



Figure 1: Smoking prevalence by age in male population. Effect of each scenario in Belgium



Figure 2: Smoking prevalence by age in female population. Effect of each scenario in Belgium

3.2 Effect of Alternative Scenarios on Healthy Life Years, Unhealthy Life Years and Life Expectancy

3.2.1 Cross-sectional Life Expectancies

The results discussed below are differences between the "what-if" or policy/intervention scenarios and the reference scenario for men and women at age of 15 in the year 2028 and 2048. Table 2 shows the impact of the scenarios on the cross-sectional health expectancies calculated for a particular calendar year, i.e. for individuals at age of 15 in 2028 and 2048.

Reference scenario or "business-as-usual" scenario

Our findings show that in 2028, 15-year-old men and women would be expected to live additional 50.07 and 51.65 years without disability and 14.04 and 17.32 years with disability. Our results also indicate a slight decrease in healthy life years over time. In 2048, 15-year-old men and women would be expected to live additional 49.97 and 51.51 years without disability and 14.01 and 17.34 years with disability.

"What-if" Scenarios

In comparison to the reference scenario, in 2028 for the male and female population, the "smoking-free population" scenario would result in an increase in HLY by 3.44 and 2.74 years, a decrease in ULY by 0.79 and 1.88 years, and an increase in total life expectancy by 2.65 and 0.86 years. By 2048, these differences become even more pronounced - HLY increases by 3.54 years in men and by 2.88 years in women; ULY decreases by 0.76 and 1.90 years in men and women, and LE increases by 2.78 years in men and 0.98 years in women.

By 2028, the "zero (re)start probabilities" scenario results in an increase in HLY and LE by 0.53 and 0.27 years, and a decrease in ULY by 0.26 years in males. For female population by 2028, HLY increases by 0.50 years, ULY decreases by 0.43 years and LE increases by 0.07 years. In 2048, the observed effect is even greater: HLY rises by 1.59 and 1.44 years, ULY is reduced down by 0.75 and 1.23 years, overall LE increases by 0.84 and 0.21 years in men and women. In the "all smokers quit" scenario, larger impact occurs already in a short run and stays almost constant over the coming years. By 2028 and 2048, men gain 1.73 and 1.74 years in HLY; 1.01 and 1.0 years in LE, and their ULY is reduced by 0.72 and 0.74 years. Women gain 1.55 and 1.58 years in HLY by 2028 and 2048; their ULY is reduced by about 1.37 and 1.40 years by 2028 and 2048. Overall LE shows a constant gain of 0.18 years in both reported years. The "zero (re)start probabilities and all smokers quit" scenario reports the highest gains among all "what-if" scenarios. In 2028, men gain 1.88 and 1.08 years in HLY and LE, and lose 0.80 years in ULY; women gain 1.67 and 0.20 years in HLY and LE, and lose 1.47 years in ULY. By 2048, this alternative scenario gains 2.25 and 1.98 years in HLY for men and women; and loses 0.93 and 1.68 years in ULY in men and women, respectively.

If Belgium had smoking prevalence of Sweden, the European country with the lowest overall smoking prevalence, the gain in terms of HLY and the reduction in ULY would be substantial for males and females in both reported years. For the 15-year-old male population, HLY would increase by 0.92 and 1.03 years, and ULY would decrease by 0.57 and 0.56 by 2028 and 2048. Their total life expectancy would increase by 0.35 and 0.47 years in 2028 and 2048. The female population would also gain some additional time in terms of HLY, 0.17 and 0.32 years, and lose time in terms of ULY by 0.40 and 0.45 years, by the years 2028 and 2048. On the contrary, the overall life expectancy would decrease by 0.23 and 0.13 years in 2028 and 2048 when compared to the total life expectancy calculated for the reference scenario.

Policy/Intervention Scenarios

By 2028, the "no smoking initiation before age 18" intervention would result in an increase in HLY by 0.03 years in men and 0.05 years in women; a decrease in ULY by 0.02 years in men and 0.04 years in women; and an increase in overall LE by 0.01 years for men and women. In the long run, these values remain the same or change slightly.

By increasing the quit probabilities by 30%, HLY at age 15 results in gains of 0.14 and 0.26 years for men by 2028 and 2048. For women these differences are 0.12 and 0.21 years, respectively. Doubling the quit probabilities yields an increase of 0.40 and 0.34 years for men and women by 2028. The gains in HLY further increase up to 0.68 and 0.57 years by 2048. In both scenarios and for both sexes, ULY decreases gradually over time with an increase in quit probabilities. Although the gain in HLY is greater among males, the reduction in ULY is more notable among females.

Table 2: Impact of "what-if" scenarios and smoking policy/interventions on healthy life years, overall life expectancy, and unhealthy life years (in years) for men and women at age of 15 in 2028 and 2048

	HLY		ULY		\mathbf{L}	Е
	2028	2048	2028	2048	2028	2048
Reference scenario Men	50.07	49.97	14.04	14.01	64.11	63.98
Difference with reference scenario						
1. Smoking-free population	3.44	3.54	-0.79	-0.76	2.65	2.78
2. Zero (re)start probabilities	0.53	1.59	-0.26	-0.75	0.27	0.84
3. All smokers quit	1.73	1.74	-0.72	-0.74	1.01	1.00
4. Zero (re)start probabilities and all smokers quit	1.88	2.25	-0.80	-0.93	1.08	1.32
5. Smoking prevalence of Sweden	0.92	1.03	-0.57	-0.56	0.35	0.47
6. No smoking initiation before age 18	0.03	0.03	-0.02	-0.01	0.01	0.02
7. 30% increase in quit probabilities	0.14	0.26	-0.04	-0.09	0.10	0.17
8. Doubling quit probabilities	0.40	0.68	-0.14	-0.25	0.26	0.43
Reference scenario Women	51.65	51.51	17.32	17.34	68.97	68.85
Difference with the reference scenario						
1. Smoking-free population	2.74	2.88	-1.88	-1.90	0.86	0.98
2. Zero (re)start probabilities	0.50	1.44	-0.43	-1.23	0.07	0.21
3. All smokers quit	1.55	1.58	-1.37	-1.40	0.18	0.18
4. Zero (re)start probabilities and all smokers quit	1.67	1.98	-1.47	-1.68	0.20	0.30
5. Smoking prevalence of Sweden	0.17	0.32	-0.40	-0.45	-0.23	-0.13
6. No smoking initiation before age 18	0.05	0.06	-0.04	-0.05	0.01	0.01
7. 30% increase in quit probabilities	0.12	0.21	-0.09	-0.18	0.03	0.03
8. Doubling quit probabilities	0.34	0.57	-0.29	-0.49	0.05	0.08

3.2.2 Cohort Life Expectancies

To see the effect of the scenarios in a cohort perspective, the cohort life expectancies were calculated. Table 3 shows the full impact of the scenarios on a cohort of 15-year-olds in 2018.

Table 3: Impact of "what-if" scenarios and smoking policy/interventions on healthy life years, overall life expectancy, and unhealthy life years (in years) of a cohort of 15-year-olds in Belgium in 2018

	Men					
	HLY	ULY	\mathbf{LE}	HLY	ULY	\mathbf{LE}
Reference scenario	49.89	14.02	63.91	51.59	17.23	68.82
Difference with reference scenario						
1. Smoking-free population	3.62	-0.78	2.84	2.79	-1.81	0.98
2. Zero (re)start probabilities	2.60	-0.56	1.84	1.96	-1.27	0.69
3. All smokers quit	1.76	-0.75	1.01	1.48	-1.30	0.18
4. Zero (re)start probabilities and all smokers quit	2.98	-0.76	2.22	2.35	-1.63	0.72
5. Smoking prevalence of Sweden	1.11	-0.57	0.54	0.29	-0.37	-0.08
6. No smoking initiation before age 18	0.03	-0.02	0.05	0.08	-0.03	0.05
7. 30% increase in quit probabilities	0.26	-0.09	0.17	0.22	-0.18	0.04
8. Doubling quit probabilities	0.74	-0.27	0.47	0.55	-0.46	0.09

Reference scenario or "business-as-usual" scenario

We have estimated that in 2018, a cohort of 15-year-old men and women would be expected to live additional 49.89 and 51.59 years without disability and 14.02 and 17.23 years with disability.

"What-if" Scenarios and Policy/Intervention Scenarios

When compared to the current cohort of never, current, and former smokers, the "smoking-free" cohort would gain 3.62 and 2.79 years in HLY indicator for men and women. Their ULY would be lowered down by 0.78 years in men and 1.81 years in women. "Zero (re)start probabilities" scenario would increase the remaining HLY in men by 2.60 years and in women by 1.96 years, and decrease the coming ULY by 0.56 and 1.27 years in men and women, respectively. If all smokers quit, men would add 1.76 years and women 1.48 years to the remaining HLY, and their ULY would be reduced by 0.75 years in men and 1.30 years in women. As expected, combination of the two scenarios would result in even a greater increase in HLY: 2.98 and 2.35 years in men and women. If Belgium had smoking prevalence of Sweden, the current cohort of 15-year-old males would add 1.11 years to their HLY and they would be expected to spend by about 0.57 years less time in ULY. The impact on female pop-

ulation is not as eminent; they would add 0.29 years to the remaining HLY and cut the number of unhealthy life years by 0.37 years. The effect of raising the legal age to buy tobacco products to 18 would not be as large as for the "what-if" scenarios, but it would still lead to an increase in HLY by 0.03 years in men and 0.08 years in women. By increasing the quit probabilities by 30%, HLY would increase by 0.26 years in men and 0.22 years in women, whilst doubling the quit probabilities would add 0.74 and 0.55 years to the remaining HLY for a cohort of 15-year-old men and women.

For the majority of the alternative scenarios the results of cohort life expectancies indicate that in terms of the HLY increase, males would benefit more than women, who would benefit more in terms of the ULY reduction.

3.2.3 Simulation Study

A small simulation study involving a manipulation of quitting probabilities by multiplying them with values between 1.0 and 2.0 in steps of 0.1 is shown in Figure 3. For both sexes, there is an evidence of health effects building up over time.

For the female population of 15-year-olds, multiplying quit probabilities by values between 1.1 and 2.0 would lead to gains in HLY that would range from 0.04 up to 0.34 years by 2028, and from 0.08 up to 0.57 years by 2048. For the 15-year-old males, the HLY gains would range from 0.05 up to 0.40 years in 2028, and from 0.10 up to 0.68 years in 2048. ULY would decrease more rapidly in the female population, showing a reduction by 0.03 up to 0.29 years in 2028; 0.07 up to 0.49 years by 2048 when multiplication factors between 1.1 and 2.0 are applied. Among the males, ULY reduction would range between 0.01 up to 0.14 in 2028, and between 0.03 up to 0.25 years in 2048 for the same multiplication factors. Combination of the greater increase in HLY and smaller reduction in ULY would lead to more considerable gain in overall health life expectancies among males.



Figure 3: Impact of an increase in quit probabilities on healthy life years, overall life expectancy and unhealthy life years among males (*left panel*) and females (*right panel*)

4 Discussion

4.1 Main Findings

To our knowledge, this was the first Belgian study aiming to compare how various "what-if" and smoking policy/intervention scenarios affect the length of HLY, ULY and overall LE of Belgium population. The comparison was done using DYNAMO-HIA, a dynamic population model, for simulating the projection of real-life population of Belgium for a period of 30 years to the future, separately for men and women. Our simulation outcomes include summary measures of population health, i.e. HLY, ULY, and LE, as well as prevalence of current, never and former smokers between the years 2018 and 2048.

Our findings confirm results of prior studies that smoking is one of the main risk factors for disability and premature mortality in male and female population [3, 39–41]. Absence of current and former smokers in the Belgian population would yield major gains in terms of HLY and total LE for a cohort of 15-year-olds, i.e. about 3.62 years in HLY and 2.84 years in overall LE in males and 2.79 years in HLY and 0.98 years in overall LE in women.

Comparisons of "what-if" and smoking/intervention scenarios with the reference scenario indicate that the gains in HLY or LE and the reduction in ULY or in smoking prevalence differ in each scenario and over the projection period. The impact under the "zero (re)start probabilities" scenario is built up over time and is more effective in the future than in the short run. Interventions preventing smoking initiation mainly focus on the never smokers among adolescents who possess low absolute risks of disability and mortality, and hence their gains in terms of health are more observable in further future as the adolescents reach later adulthood.

On the contrary, the smoking control policies focusing on smoking cessation, potentially introduced by the "all smokers quit" scenario, result in larger gains in HLY and LE in the first years after the interventions are implemented and their effect size remains almost constant over the next 30 years. These results confirm the findings by Kulik et. al. that intervention/policies targeting smoking cessation are more effective in the short and long-term than programs focusing on the prevention of smoking initiation [42]. Our results also showed that policy/intervention methods combining the prevention of smoking initiation with the smoking cessation programs are the most effective among all the alternative scenarios, yielding the largest decrease in the smoking exposure and in ULY as well as the largest increase in HLY. The reduction in ULY is even greater for the "zero (re)start probabilities and all smokers quit" scenario than for the "smoking-free population" scenario between the years 2018 and 2048. A possible explanation is that individuals in the smoking-free population without any smoking histories accumulate more unhealthy years over their prolonged overall life course than individuals in a population consisting of never and former smokers. The fact that a combination of two different potential strategies for eradication of smoking is the most effective one is supported by findings from Rose that policies targeting the whole population are often the most effective ones [43].

Our results also indicate that an implementation of a nationwide policy raising the legal age limits to buy tobacco products from 16 to 18 would contribute to a reduction in smoking prevalence among young people and in turn to an increase in HLY and LE. These claims support findings of Fidler and West who investigated the impact on smoking prevalence after raising the minimum age of legal access to tobacco products from 16 to 18 in 2007 in England [44]. As adolescence is a sensitive developmental period, many risk factor behaviors peak during this time [45, 46]. Preventing young people from experimenting with tobacco products when they are the most vulnerable should become the main objective of the policy makers in the government.

4.2 Strengths and Limitations

An important strength of our study is the use of a nationally representative data from the Belgian population. Added value to this study also includes the use of disability indicator based on the GALI, allowing better comparability with international studies that use the same instrument. Nevertheless, the key strength of our study relates to the use of a dynamic modeling tool exclusively developed for health impact assessment. DYNAMO-HIA software can distinguish different risk factor states in order generate the transition probabilities between these states necessary for modeling the impacts of various interventions/policies on population health.

Our study has several limitations that must be considered when interpreting the results. Self-reported data on disability and smoking behavior were obtained from a cross-sectional survey and thus, assessing the causal relationship between smoking and disability prevalence may cause temporal bias. Also, selection bias and underestimating of the true smoking exposure may occur due to the low response rate in BHIS 2013 and due to the exclusion of individuals with missing information on smoking or the GALI.

The BHIS 2013 did not provide information on time since quitting for the former smokers; hence the OR quantifying the association between smoking and disability does not take into account such information. Prior studies report conflicting findings on the impact of smoking cessation on disability. Some suggest that former smokers have similar disability hazards as current smokers, whilst others suggest that the smoking duration and time since quitting significantly affect the health-related quality of life and need to be considered [3, 4, 47].

We calculated health expectancies by Sullivan's method. This approach assumes constant transition rates between disability states and their rapid and sudden changes in the observed period may lead to biased results [48]. Prior studies showed that the Sullivan method cannot detect sudden changes in disability transition rates, but can still provide good estimates if the changes in disability prevalence are smooth and relatively regular over longer period of time [49].

The main drawback of our study is the lack of uncertainty quantification provided by DYNAMO-HIA. In its current form, the software does not include the probabilistic sensitivity analysis as its implementation into the model would be time consuming and cost intensive [17]. DYNAMO-HIA, however, provides an option of conducting one-way sensitivity analysis, by enabling easy manipulation of all input parameters.

5 Conclusion

Our findings provide a valuable insight into better understanding of how various smoking policies/interventions affect HLY, ULY and LE. We showed that the nationwide anti-smoking policies/interventions, combining the prevention of smoking initiation with the smoking cessation programs, are the most beneficial in reducing smoking prevalence and in turn increasing HLY and decreasing ULY in both the short and long run. Future research should explore the role of frequency of smoking and time since quitting in the impact of tobacco control interventions on health expectancies. Nonetheless, we can conclude that all modeled smoking policies/interventions reduce the prevalence of smoking and prolong the years without disability.

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Appendix Α

Tables A.1

Table A1: Comparison of six reviewed models against the evaluation criteria defined by DYNAMO-HIA consortium

	Criteria						
	Arbitrary				\mathbf{Rich}	ו יינו מ	Technical
Models	risk factor	Real-life	Real-life Dynamic	Modest	model	Publicly	knowledge
	states	population	projection	data input	output		required
ARMADA	yes	yes	yes	no	no	no	no
GBD	no	no	no	yes	no	yes	no
POHEM	yes	yes	yes	no	yes	no	no
PREVENT	yes	yes	no	yes	yes	no	no
MSLT	no	no	no	yes	yes	yes^1	no
RIVM CDM	yes	yes	yes	no^1	yes	no	yes

 1 With limitations

ARMADA(Age-Related Morbidity and Death Analysis); GBD(Global Burden of Disease); POHEM(Population Health Modeling); MSLT(Proportional Multi-State Life Table); RIVM CDM(National Institute for Public Health and the Environment, then Netherlands, Chronic Disease Model) source: DYNAMO-HIA consortium [18]

Table A2: Summary table for second degree fractional polynomials used for estimating the smoking prevalence in Belgium.

Model	p_1	p_2	Deviance	AIC
Model 1: Prevalence of never smokers	-0.5	3	7985.0	7993.0
Model 2: Prevalence of current smokers	-2.0	3	6362.6	6370.6
Model 3: Prevalence of former smokers	0.5	3	5818.9	5826.9

	OR current	95% CI	p-value	OR former	95% CI	p-value
Men	1.78	1.32; 2.42	< 0.001	1.14	0.85; 1.53	0.38
Women	2.31	1.72; 3.11	< 0.001	1.21	0.87; 1.68	0.27

Table A3: Odds ratios quantifying the association between smoking and disability

 Table A4: Relative risks quantifying the association between smoking and mortality

	RR current smoker	RR former smoker
Men	2.13	1.35
Women	1.42	1.23

A.2 Figures



Figure A1: Prevalence of never, current and former smokers by age and gender in Belgium



Figure A2: Prevalence of never, current and former smokers by age and gender in Sweden



Figure A3: Prevalence of disability, based on GALI, by age and gender

A.3 R codes

```
##### Settings #####
## required packages
library(ggplot2)
library(survey)
library(mfp)
library(rJava)
library(xlsxjars)
library(xlsx)
library(knitr)
library(splines)
# read data
dta <- read.csv2("../02_data/his2013_otavova.csv")</pre>
## clean data
dta <- subset(dta, wfin != -3)</pre>
dta <- subset(dta, sh03 != -3)
dta <- subset(dta, sh03 != -1)
dta <- subset(dta, !(TA06_1 %in% c(-3,-1)))</pre>
dta$sex <- factor(dta$hc04, labels = c("male", "female"))</pre>
dta$age <- dta$hc_01
dta$smoking <- ifelse(dta$TA06_1 == 4, 1,</pre>
                        ifelse(dta$TA06_1 %in% c(1,2), 2, 3))
dta$smoking1 <- factor(dta$smoking, labels=c("never","current",</pre>
                                                     "former"))
dta$sh03 <- ifelse(dta$sh03 %in% 1:2, "disabled", "healthy")</pre>
dta$sh03 <- factor(dta$sh03, levels = c("disabled", "healthy"))</pre>
# create 3 response variables
dta$smoN <- ifelse(dta$smoking1 == "never", 1, 0)</pre>
dta$smoC <- ifelse(dta$smoking1 == "current", 1, 0)</pre>
dta$smoF <- ifelse(dta$smoking1 == "former", 1,0)</pre>
# design of the HIS study
his <-
  svydesign(id = ~hh_cluster,
            strata = ~provw,
            weights = ~wfin,
```

data = dta)


```
# Never smokers
n \leftarrow mfp(smoN == 1 ~ fp(age, df = 4, select = 0.05) + sex,
                                     family = "binomial", data = dta)
model0 <- svyglm(I(smoN == 1) ~ I((age)^-0.5)+I((age)^3)+sex,</pre>
                             design = his, family = quasibinomial())
# Current smokers
c \leftarrow mfp(smoC == 1 ~ fp(age, df = 4, select = 0.05) + sex,
                                   family = "binomial", data = dta)
model1 <- svyglm(I(smoC == 1) ~ I((age)^{-2}) + I((age)^{3})+sex,
                             design=his, family = quasibinomial())
# Former smokers
f \leftarrow mfp(smoF == 1 ~ fp(age, df = 4, select = 0.05) + sex,
                                     family = "binomial", data = dta)
model2 <- svyglm(I(smoF == 1) ~ I((age)^0.5) + I((age)^3)+sex,</pre>
                            design = his, family = quasibinomial())
## predict smoking prevalence by age and sex
new <- expand.grid(age = 15:95, sex = c("male", "female"))</pre>
pred <-
  rbind(
    cbind(new, smo = "N", p = predict(model0, new,
                                                type = "response")),
    cbind(new, smo = "C", p = predict(model1, new,
                                                type = "response")),
    cbind(new, smo = "F", p = predict(model2, new,
                                               type = "response")))
colnames(pred)[4] <- "p"</pre>
pred <- pred[,-5]</pre>
pred$sex <- factor(pred$sex, levels = c("female", "male"))</pre>
levels(pred$smo) <- c("Never", "Current", "Former")</pre>
# plot
smok <- ggplot(pred, aes(x = age, y = p)) +</pre>
  geom_line(aes(col = sex)) +
  facet_grid(~smo) +
```

```
theme_bw()
smok + scale_x_continuous(name = "Age", limits = c(15,95)) +
  scale_y_continuous(name = "Proportion", limits = c(0, 1))
smoALL <-</pre>
 reshape(
   pred,
   idvar = c("age", "sex"),
   timevar = "smo",
   direction = "wide")
smoALL$p <- rowSums(smoALL[, 3:5])</pre>
smoALL$pn.N <- (smoALL$p.Never / smoALL$p)*100</pre>
smoALL$pn.C <- (smoALL$p.Current / smoALL$p)*100</pre>
smoALL$pn.F <- (smoALL$p.Former / smoALL$p)*100</pre>
smoALL <- smoALL[,-c(3:6)]
#### final smoking prevalence ####
write.xlsx(smoALL, "F:/03_analyses/his2013_prevalence.xlsx",
          append = FALSE, col.names = TRUE, row.names = TRUE)
model <- svyglm(sh03 == "disabled" ~ age + sex,</pre>
                design = his, family = quasibinomial())
new <- expand.grid(age = 0:95, sex = c("male", "female"))</pre>
pred <-
 rbind(
   cbind(new, smo = "Disability", p = predict(model, new,
                                    type = "response")))
pred$sex <- factor(pred$sex, levels = c("female","male"))</pre>
# plot
dis <- ggplot(pred, aes(x = age, y = p.response)) +
 geom_line(aes(col = sex)) +
 facet_grid(~smo) +
 theme_bw()
dis + scale_x_continuous(name = "Age") +
  scale_y_continuous(name = "Proportion", limits = c(0, 1))
```

```
pred$p.response <- pred$p.response*100</pre>
#### final disability prevalence ####
write.xlsx(pred, "F:/03_analyses/his2013_disability_prevalence.xlsx",
                  append=FALSE, col.names=TRUE, row.names=TRUE)
#### male ####
male <- subset(dta, dta$sex == "male")</pre>
# design of the HIS study
his <-
 svydesign(id = ~hh_cluster,
          strata = ~provw,
          weights = ~wfin,
          data = male)
model0 <- svyglm(sh03 == "disabled" ~ age + smoking1, design=his,</pre>
                                   family = quasibinomial())
#### female ####
female <- subset(dta, dta$sex == "female")</pre>
# design of the HIS study
his <-
 svydesign(id = ~hh_cluster,
          strata = ~provw,
          weights = ~wfin,
          data = female)
model1 <- svyglm(sh03 == "disabled" ~ age + smoking1, design=his,</pre>
                                   family = quasibinomial())
****
###### SMOOTHING SMOKING PREVALENCE OF SWEDEN ####
prevalence <- read_excel("Smoking_prevalence_Sweden.xlsx")</pre>
attach(prevalence)
```

```
r<-c(16:95)
agelims = range(r)
age.grid = seq(from = agelims[1], to = agelims[2])
#### female prevalence ####
female <- subset(prevalence, prevalence$sex == "female")</pre>
# Never smokers
female_never = lm(never ~ ns(age, df = 8), data = female)
predict_female_never = predict(female_never,
                         newdata = list(age = age.grid), se = T)
a<-predict_female_never$fit
# Current smokers
female_current = lm(current ~ ns(age, df = 8), data = female)
predict_female_current = predict(female_current,
                         newdata = list(age = age.grid), se = T)
b<-predict_female_current$fit</pre>
# Former smokers
female_former = lm(former ~ ns(age,df = 8), data = female)
predict_female_former = predict(female_former,
                        newdata = list(age = age.grid), se = T)
c <- predict_female_former$fit</pre>
age <- c(16:95)
smooth_prevalence <- data.frame(a,b,c)</pre>
sum_row <- rowSums(smooth_prevalence, dims = 1)</pre>
smooth_prevalence <- data.frame(a,b,c,sum_row)</pre>
attach(smooth_prevalence)
smooth_prevalence$never <- (a/sum_row)*100</pre>
smooth_prevalence$current <- (b/sum_row)*100</pre>
smooth_prevalence$former <- (c/sum_row)*100</pre>
smooth_prevalence <- smooth_prevalence[,5:7]</pre>
new <- expand.grid(age = 16:95, sex = c("female"))</pre>
smooth_prevalence_complete <- data.frame(smooth_prevalence,new)</pre>
#### male prevalence ####
male <- subset(prevalence, prevalence$sex == "male")</pre>
```

```
# Never smokers
male_never = lm(never ~ ns(age, df = 8), data = male)
predict_male_never = predict(male_never,
                         newdata = list(age = age.grid), se = T)
a <- predict_male_never$fit</pre>
# Current smokers
male_current = lm(current ~ ns(age, df = 8), data = male)
predict_male_current = predict(male_current,
                        newdata = list(age = age.grid), se = T)
b <- predict_male_current$fit</pre>
# Former smokers
male_former = lm(former ~ ns(age,df = 8), data = male)
predict_male_former = predict(male_former,
                    newdata = list(age = age.grid), se = T)
c <- predict_male_former$fit</pre>
age <- c(16:95)
smooth_prevalence <- data.frame(a,b,c)</pre>
sum_row <- rowSums(smooth_prevalence, dims = 1)</pre>
smooth_prevalence <- data.frame(a,b,c,sum_row)</pre>
attach(smooth_prevalence)
smooth_prevalence$never <- (a/sum_row)*100</pre>
smooth_prevalence$current <- (b/sum_row)*100</pre>
smooth_prevalence$former <- (c/sum_row)*100</pre>
new <- expand.grid(age = 16:95, sex = c("male"))</pre>
smooth_prevalence_complete1 <- data.frame(smooth_prevalence, new)</pre>
#### final Swedish smoking prevalence ####
pred <- rbind(smooth_prevalence_complete,</pre>
                                        smooth_prevalence_complete1)
write.xlsx(pred,"F:/Prevalence Sweden/
      smooth_Swedish_smoking_prevalence.xlsx", append = FALSE,
                               col.names = TRUE, row.names = TRUE)
# plot
pred <- read_excel("Sweden_smoking_plot1.xlsx")</pre>
pred$sex <- as.factor(pred$sex)</pre>
pred$p <- pred$p/100</pre>
```

```
p <- ggplot(pred, aes(x = age, y = p)) +
           geom_line(aes(col = sex)) +
              facet_grid(~smo) +
                 theme_bw()
p + scale_x_continuous(name="Age", limits=c(15,95)) +
           scale_y_continuous(name="Proportion", limits=c(0, 1))
###### TRANSITION PROBABILITIES MANIPULATION ####
setwd("~/Dropbox/2018UH_Martina/02_data/XML")
# required packages
library(XML)
library(methods)
# helper function
dataFrameToXML <-
  function(df, file) {
   xml <- xmlTree()</pre>
   suppressWarnings(xml$addTag("transitionmatrix", close=FALSE))
   for (i in seq(nrow(df))) {
     xml$addTag("transition", close=FALSE)
     for (j in names(df)) {
       xml$addTag(j, df[i, j])
     }
     xml$closeTag()
   }
   xml$closeTag()
   saveXML(xml, file = file)
  }
# read file
df <- xmlToDataFrame("Transitions_fixed.xml", rep("numeric", 5))</pre>
# check values
with(df, tapply(percent, list(age, sex, from), sum))
subset(df, from == 1 & to == 3) # should be zero
subset(df, from == 2 & to == 1) # should be zero
subset(df, from == 3 & to == 1) # should be zero
#### no one (re)starts ####
```

df2<-df

df2[df2\$from == 1 & df2\$to == 2,]\$percent <- 0 df2[df2\$from == 1 & df2\$to == 1,]\$percent <- 100 df2[df2\$from == 3 & df2\$to == 2,]\$percent <- 0 df2[df2\$from == 3 & df2\$to == 3,]\$percent <- 100 dataFrameToXML(df2, "Transitions_No_One_Restarts.xml") #### everyone quits #### df2<-df df2[df2\$from == 2 & df2\$to == 2,]\$percent <- 0 df2[df2\$from == 2 & df2\$to == 3,]\$percent <- 100 df2[df2\$from == 3 & df2\$to == 2,]\$percent <- 0 df2[df2\$from == 3 & df2\$to == 3,]\$percent <- 100 dataFrameToXML(df2, "Transitions_Everybody_Quits.xml") #### no one starts, everybody quits #### df2<-df df2[df2\$from == 1 & df2\$to == 2,]\$percent <- 0 df2[df2\$from == 1 & df2\$to == 1,]\$percent <- 100 df2[df2\$from == 2 & df2\$to == 2,]\$percent <- 0 df2[df2\$from == 2 & df2\$to == 3,]\$percent <- 100 df2[df2\$from == 3 & df2\$to == 2,]\$percent <- 0 df2[df2\$from == 3 & df2\$to == 3,]\$percent <- 100 dataFrameToXML(df2, "Transitions_No_one_starts_everybody_Quits.xml") #### 30% increase in quit probabilities #### ## this code can be used for the small simulation study when quit ## probabilities are multiplied by values between 1.1 and 2.0 df2<-df df2[df2\$from == 2 & df2\$to == 3,]\$percent <-1.3*(df2[df2\$from == 2 & df2\$to == 3,]\$percent) df2[df2\$from == 2 & df2\$to == 2,]\$percent <-

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Richting: Master of Statistics-Epidemiology & Public Health Methodology Jaar: 2018

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Otavova, Martina

Datum: 15/06/2018