This project has received funding from the European Union's Horizon 2020 research and innovation programme under grant agreement No 774548.

EC Framework Programme for Research and Innovation

Horizon 2020
H2020-SFS-2017-2-RIA-774548-STOP:
Science & Technology in childhood Obesity Policy

Science & Technology in childhood Obesity Policy

Start date of project: 1st June 2018 Duration: 48 months

D9.3: Report on results of simulations of policy options

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Version: Final

Preparation date: 05/11/2021

Dissemination Level

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Science and Technology in childhood Obesity Policy

Abbreviation	Definition
STOP	Science and Technology in childhood Obesity Policy
SSB	Sugar sweetened beverage
FOP	Front of Pack
BMI	Body Mass Index
DALY	Disability-adjusted Life years
YLL	Years of Life Lost
YLD	Years Lived with Disability
MET	Metabolic Equivalent
EBM	Energy Balance Model

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1 Overview

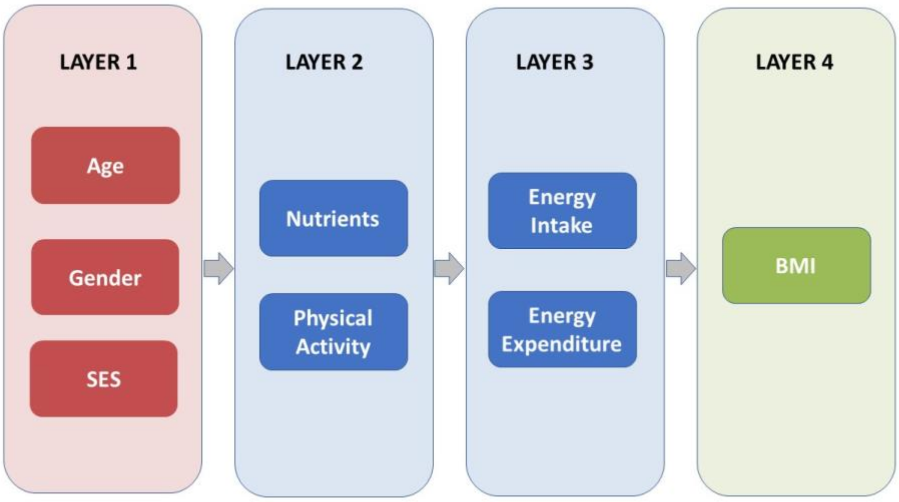
This report provides a proof-of-concept of the STOP Policy Simulation Tool. The main objective is to demonstrate the capacity of the STOP software in simulating the effect of policy interventions on health outcomes relative to a baseline scenario (status quo). This report describes simulations from the STOP model which provide evidence that can help policy makers assess the feasibility and effectiveness of interventions to tackle childhood obesity. This is illustrated with simulations on one policy intervention – regulation of marketing of food products to children. The aim is to show how the model works and the kind of outcomes it can produce. It does not provide a set of final results of policy interventions. In the remaining months of the project, simulations for other policy options will be further developed and a full picture of their impact will be presented to assess the feasibility and effectiveness of such policies.

1.1 STOP simulation framework

The STOP Policy Simulation Tool is based on a modular and flexible microsimulation framework allowing researchers to test the effectiveness of a variety of health policies and interventions in tackling childhood obesity. The model simulates close-to-reality life histories from birth to death of each member of a population including key characteristics such as gender, age, socio-economic status, risk factors, and disease profiles. These characteristics evolve over time and are updated annually using statistical and probabilistic models which are calibrated to reproduce key demographic and epidemiological statistics from European countries. The tool uses statistical models taking into account a variety of complex interactions such as risk factor-disease interactions and disease-disease interactions. Modellers are then able to evaluate health-related policies by changing some of the parameters and comparing the outputs with a baseline simulation. At the end of the simulation, the tool produces very detailed quantitative outputs covering demographics, risk factors, diseases, mortality, and health care expenditure which could then be used to complement qualitative policy evaluation tools.

1.2 Energy balance model

National dietary surveys from various European countries were analysed with a view to building a comprehensive model of childhood obesity. The model estimates yearly changes in physical activity, diet, energy balance, and body mass index (BMI) using statistical models calibrated using dietary and anthropometric surveys from a given country. These dynamics include measures of physical activity expressed in metabolic equivalents (METs) and macronutrients intakes measures including grams of fat, carbohydrates, protein, fibre, salt, and sugar. The calibration of the equations is carried out by gender for children and adults separately to ensure capturing gender- and age-related differences. Emphasis is placed on capturing the rapid growth and changes in children BMIs. International anthropometric references are used to properly classify individuals as normal weight, overweight or obese. This is a key step as this classification is used throughout the simulation to identify children with growth problems and devise appropriate policies and interventions to tackle the health issues.



At the beginning of each simulation, the tool assigns individuals a starting physical activity level, dietary intake, Body Mass Index, and diseases by sampling from national representative surveys. As people age, their calorie intake and activity levels change as well, and statistical equations are used to predict these changes over the course of the simulation. These changes in the energy balance will then be converted into a change in Body Mass Index (BMI) using the Energy Balance Model (EBM) equations. The model accounts for the effects of both risk factors and diseases in changing the likelihood of acquiring new diseases.

Machine learning algorithms are used to calculate the burden of diseases in terms of health care expenditures, disease incidence, and mortality. At the end of the simulation, the tool will aggregate various primary outputs to produce detailed and granular data about the impact of health policies. By comparing these outputs, decision-makers would be able to identify the best interventions in tackling childhood obesity.

2 Approach for policy evaluation

The overall approach adopted to evaluate the impacts and cost-effectiveness of intervention policies to reduce childhood obesity using the policy simulation tool is based upon “what-if” analyses to quantify the causal relations between variables. The analysis defines “scenarios” to represent expectations about possible future trends and quantify potential responses to new events or policies to tackle childhood obesity. This approach for policy evaluation is well documented in the literature (Emmert-Fees et al., 2021), and in simple terms, scenarios can be classified as:

- *Baseline scenarios*: elaborated to define the trends in observed childhood obesity we measure outcomes against (e.g., population, calories intake, diseases prevalence trends).
- *Intervention scenarios*: policies designed to change the observed trends in childhood obesity during a specific timeframe (e.g., food labelling, healthy eating promotion, BMI reduction).

The choice of baseline scenario is critical for analyses as it serves as a reference for comparison and can influence outcomes. While other models use country-specific demographic data, we decided to use the UN World Population Database (UN, 2019), which is freely available for and provides consistent data for most countries in the world from 1950, with projections to 2100, covering a variety of demographic metrics, both estimates and projections by gender and age-groups. This is important in cross-countries comparisons as the same methodology was applied in generating the data for all world regions and countries, furthermore, the wider researcher community can have access to the same high-quality data and is able to verify and reproduce the published results.

Having carefully defined the baseline scenario, the microsimulation assesses the impacts of different intervention policies by projecting populations, risk factors, diseases, and life trajectories into the future comparing pairs of no-intervention and intervention scenarios. The first run evaluates the no-intervention, “baseline scenario” where demographics, risk factors, and diseases are projected based solely on estimates from historical data. The second run evaluates the “intervention scenario” where a specific policy is applied to the same population with the aim of modifying the underlying trends and risk factor distribution.

Finally, the tool compares the two simulated scenarios results in terms of population demographics and burden of diseases to estimate the cost-effectiveness and impacts of the targeted intervention.

3 Policy areas

Our report analyses policy scenarios in six policy areas, identified based on the work undertaken in STOP WPs 4 to 8. The areas we have selected are among those addressed in the above WPs for which sufficient evidence exists of the effectiveness of specific policies in improving children’s diet or physical activity behaviours. These are also the policy areas in which STOP will develop WP9 policy briefs and toolkits, according to the project plan.

3.1 Policy interventions

The array of policy interventions we evaluate includes fiscal measures, front-of-package labelling, mandatory regulations on marketing, food reformulation of unhealthy products, nudges in school to modify food choices, and school-based interventions to promote physical activity. In this report, we present simulations for one intervention: mandatory regulations on marketing. The aim is to show how the model carries out its simulations and the type of outputs it can produce. In order to simulate the effect of these interventions, we use evidence drawn from the STOP systematic reviews together with evidence from other sources.

3.2 Fiscal measures

To date, several European countries have introduced fiscal measures to reduce the consumption of unhealthy products. Several countries have implemented taxes on sugar-sweetened beverages (SSB); however, taxes on food products high in sugar, such as sweet snacks and confectionery are rare. Evidence from studies looking at the impact of this type of measures on SSB and high sugar products suggest a beneficial effect on purchases, consumption, and health outcomes (STOP WP4 Deliverable D4.1.a).

The fiscal intervention estimated in the model consists of a 20% tax increase on SSB. It is assumed that this tax rate is fully passed to the consumer through an increase of 20% of prices. The products eligible to be taxed include all drinks containing added sugar; that is, soft drinks, sports drinks, energy drinks, fruit juices, sugar-sweetened milk, vegetable drinks, and flavoured water. The STOP microsimulation model uses estimates from STOP WP4 Deliverable D4.2 to produce simulations of the effect of SSB taxes on several outcomes.

Most studies examining the impact of fiscal measures on consumption have focused on adult behaviour. However, STOP WP4 Deliverable D4.2 produced a set of estimates for children (0-9-year-olds) and adolescents (10–17-year-olds) that we use in our models. The D4.2 report produced estimates of the effect of SSB taxes on children’s nutrient intake in five European countries: Finland, France, Italy, Spain and the United Kingdom. Their estimates account for both own- and cross-price elasticities as well as for dietary intake over different food categories (STOP WP4 Deliverable D4.2) (see Table 1). For this deliverable, we concentrate on the effect on calorie intake. Table 1 shows that a 20% increase in SSB prices results in a decline in children's and adolescents' calorie intake, especially in Finland, France and Spain. For adults, we calculated the percentage change in calorie intake using price elasticities of the SUSDIET project (Akaichi et al., 2017); dietary intake information from the EFSA Comprehensive Food Consumption Database (EFSA, 2011); and information on the contribution of calories to different food categories from Our World in Data. We obtained negative values for Finland, Italy and Spain, and small but positive values for France and the UK. This positive effect is due to a substitution for dairy products and composite dishes in France and for grains and grain-based products in the UK. Akaichi et al., (2017) noted that the level of heterogeneity in price elasticities was expected given the strong cultural influences on food consumption across Europe. These findings show the need to conduct country-specific analyses to inform policies aimed at improving diets. Thus, at this stage, the effect of the five countries analysed here have not been generalised to other EU countries. Careful considerations and assumptions will be made to conduct such a task.

The percentage change in calories estimated above is used in the models to assess the impact on energy intake, BMI and other diseases. The model assumes that children between 0 and 9 years have a certain reduction in calories (reached at age X+1 and then constant until age 9); similarly, children between 10 and 17 experience a certain reduction in calories (reached at age X+1 and then constant until age 17); and when children reach the age of 18, it is assumed that they have another specific change in their calorie intake, which remains constant over their life-course. The change in calorie intake per age group differs by country (see Table 1).

Systematic reviews have reported considerable heterogeneity between and within studies (Teng et al., 2019). Differences in results are explained by several factors including tax design as well as context and family circumstances (Akaichi, et al 2017)). The microsimulation model aims at accounting for such differences. However, now, there is scarce evidence on the factors behind these differences that can be used to feed our models. An important aspect we have available to consider in our simulations is price elasticity differences by social class. We use estimates produced by STOP WP4 Deliverable D4.2 on price elasticities by income level for France and extrapolated differences by socioeconomic groups to other countries. We calculated ratios to the average elasticity for each income level in France and applied such ratios to the average effect of other countries obtaining estimates by income class (See Table 2).

Table 1. Percentage of quantity change in calorie intake for children, adolescents and adults if SSBs tax of 20% is implemented

	Children: Age 0-9	**Adolescents: Age 10-17**	**Adults**
Country	**SSBs Tax Effect**	**SSBs Tax Effect**	**SSBs Tax Effect**
	+20% in price	**+20% in price**	**+20% in price**
Finland	-1.282	-1.814	-0.125

France	-1.742	-1.812	0.777
Italy	-0.029	-0.08	-0.882
Spain		-2.988	-0.874
UK	-0.496	-0.716	0.052

Source: For children and adolescents: STOP WP4 Deliverable D4.2. For adults: own calculations based on Akaichi et al. (2017)

Table 2. Own-Price Elasticities across income class for France

Country	**Income class**		**SSB**	Ratio to **average** elasticity SSB
France	Well-off	>= €3,000	-1.135	0.991
France	Average upper	€2,000-€2,999	-1.144	0.999
France	Average lower	€1,000-€1,999	-1.205	1.052
France	Modest	<€999	-1.277	1.115
France	**Average**		**-1.145**	

Source: STOP WP4 Deliverable D4.2

Four out of the five countries examined have already implemented SSB taxes to reduce sugar consumption: Finland, France, Spain (Catalonia) and the UK. Our baseline model considers that the demand of SSBs has already been affected by the change in prices of fiscal policies already in place. We use estimates of studies evaluating the effect of SSB taxes on prices in these countries (Capacci et al., 2019; Scarborough et al., 2020; Vall Castelló & Lopez Casasnovas, 2020). Table 3 shows the mean increase in prices due to tax implementation. In the case of the UK, Finland and France, these taxes were associated with an increase in prices of around 6%. In the case of Spain (Catalonia), prices increased by 15%. We applied these estimates of price changes to the nutrient price elasticities to obtain the change in calorie intake due to the already implemented policies.

Table 3. Characteristics of fiscal measures in place

	UK	**France**	**Spain (Catalonia)**	**Finland**
Year implemented	2018	2012 **(2018: banded tax structure)**	2017 **(2020: level changed)**	1940 (most recent change in 2014)
Drinks	Drinks containing added sugar, except fruit juices and milk-based drinks	Drinks containing added sugar and artificial sweeteners	Drinks containing added sugar	All non-alcoholic beverages apart from milk
Design	Two-tiered sugar content:	Banded tax structure:	Two-tiered sugar content:	Banded for >5g sugar

	<5g: 0	**< 1g:€ .03** **>11g: €0.20**	<5g: 0	
	5-8g: £0.18		5-8g: €0.08 **€0.10**	
	>8g: £0.24		>8g: €0.12 **€0.15**	
Tax p/L	Up to £0.24 per L	€0.0716 per L	Up to €0.12 per L	Up to €0.22 per L
Pass-through	Industry	Industry	Tax must be fully passed through to consumers	Excise tax
Pass-through	0.3	39%-66%	1	36%-52%
Mean px increase	£0.075 per L (in high levy category)	€0.05-€0.09 per L		€ 0.13
Mean px increase to consumer	5.6%	4.7%-8.8%	15%	6%
Px p/L before implementation	£1.35	€ 1.08	€1.43 two litres	

The model assumes that the tax effect remains constant over the period analysed. The lack of long-term evaluations of current interventions does not allow using estimates on the effectiveness over time. Available evidence comes from evaluations of the SSB tax in Mexico suggest that the effect in reducing SSB purchases increased over the first year of implementation and that is stabilised in the second year (-9.7% and -5.5%, respectively) (Colchero et al., 2015). The model could simulate changes in the effectiveness of the intervention following a similar pattern: effect becoming stronger during the first year and then remaining constant or fading out as time passes by.

At this stage, no assumptions are made as to what specific measures should be taken to achieve the simulated price change. The model shows the impact of a 20% increase in prices due to the implementation of a SSB tax. This is the recommended level and value used in STOP WP4 Deliverable D4.2 for their simulations. The model, however, allows investigating different tax levels. Available evidence suggests that, for taxation to be effective, prices need to increase by at least 10% (Teng et al., 2019; Akaichi, et al 2017; WHO, 2016; WHO, 2015; Niebyslki et al., 2015). Hence, in the next deliverable, the model will test the effect of other tax levels.

The model considers that the amount of the tax that is passed through to the consumer is the full 20%. Available evidence on the effect of SSB taxes suggests that price increases are generally passed on to the consumer, but the pass-on-rate is not necessarily the full tax (Scarborough, 2020). Countries or jurisdictions with a mandatory full pass-through – such as Catalonia and Mexico – are more likely to pass on the full price increase to the consumer. In the case of Catalonia, it is estimated that the mandatory full pass-through was linked with a mean increase of prices of 15% (Vall Castelló & Lopez Casasnovas, 2020). By contrast, in the UK, where the tax is pass-through is to the industry, the price of high-sugar drinks increased only by 30% the amount of the tax and prices of low-sugar drinks increased by smaller amounts (Scarborough et al., 2020).

In the next stage, the model will allow assessing different tax designs. One of the fiscal interventions proposed for modelling consists of a SSB tax with a three-banded structure, whereby the tax rate increases across bands depending on sugar content, like the one adopted by the UK and Spain (Catalonia). Banded structures linked to sugar content have shown to be effective in providing incentives to reformulate beverages (Popkin & Ng, 2021; Scarborough et al., 2020). In the UK, over 50%

of manufacturers reduced the level of sugar in their beverages to move to a lower tax band, as a result of the SSB tax structure (STOP WP4 Deliverable D4.1.a). Although this is a desired outcome, evidence also suggests that there has been no change in the volume of SSB purchases in the UK after the implementation of the SSB tax. It is thus of interest to compare this tax design with one with a flat rate linked to the volume of the drink.

It is assumed that the intervention will be implemented between 2020 and 2050.

3.3 Regulation of front-of-package food labelling

Front-of-package nutrition (FOP) labelling is an emerging policy area to support policies to prevent obesity. At present, the European Commission has concluded that it is appropriate to introduce a harmonised mandatory front-of-pack nutrition labelling at the EU level. It is currently assessing different FOP options with the aim of adopting a FOP proposal by the end of 2022. The STOP microsimulation model will examine the effects of a comprehensive use of FOP labels in line with the different approaches that the EU is considering adopting as mandatory.

For this deliverable, the modelled intervention consists of mandatory FOP labelling in all processed foods. We use evidence of the effectiveness of different types of FOP labels in changing consumer choices from existing systematic reviews. This evidence suggests a beneficial effect on purchasing and consumption, especially if the format is easily understood (STOP WP4 Deliverable D4.1). Other studies consistently predict healthier dietary intakes under FOPL schemes, though most of these findings are drawn from data simulations of the potential impact on nutrient intake (WHO systematic review on nutrition labelling policies). Further, it seems that the effect on consumer behaviour varies across groups: the greatest impact is observed among nutrition-conscious and health-concerned consumers (STOP WP4 Deliverable D4.1.a).

The model assumes that the FOP intervention reduces the consumption of daily calorie intake by 1.03%. This value is drawn from a recent meta-analysis examining the impact of FOP labelling on purchases and consumption (Croker et al., 2020). This parameter is in line with estimates from the OECD that suggest that FOP labels are associated with a reduction of the daily calorie intake of 1.16% (OECD, 2019).

In the simulation, it is assumed that this 1% reduction applies across countries, different age groups and socioeconomic groups. To date, there is no evidence from STOP systematic reviews or other sources that can be used to account for differences in the use of labels or of the effectiveness of labelling schemes across different socioeconomic groups. A systematic review, conducted by WP4, did not find studies examining the effect of food labelling policies by socioeconomic background (STOP WP4 Deliverable D4.1). Further, a meta-analysis on food labelling effects on consumer diet behaviours found no significant heterogeneity by country, age, sex, socioeconomic status, or whether labelling is voluntary or mandatory (Shangguan et al., 2019).

The eligible population in this intervention is all individuals aged one year and older. It is assumed that children are affected by the purchases done by their parents. Among the eligible population, only a small share reads and uses labels when doing food purchases. Evidence from a study conducted in six European countries suggested that 16.8% of shoppers look at nutrition labels when buying food items (Grunert et al., 2010). One study assessing the use of four different labelling types observed that less than 40% of participants in the study read labels. The largest share was for nutrient declaration (39%), followed by FOP (29%). (WHO systematic review on nutrition labelling).

The STOP microsimulation model assumes that 29% of the eligible population benefits from this intervention.

In terms of the effectiveness of this policy over time, there is no evidence that allows making assumptions on this parameter. It is thus assumed that the effect remains constant over time. It is assumed that the intervention will be implemented between 2020 and 2050.

3.4 Regulation of the marketing of food products to children

Few European countries have implemented a policy to regulate food advertising to children. The UK was one of the first countries in the world to develop restrictions on the promotion of unhealthy food products to children and young people. Marketing restrictions on high in fat, salt and sugar (HFSS) products started in 2007, with the aim of limiting children's exposure to food advertising on television. Since then, restrictions have been extended to other channels such as online and social media.

The STOP model will use the UK's regulatory marketing as a policy scenario to simulate the effect of this type of policy interventions and will extend it to other EU countries. The intervention consists of a statutory ban on marketing targeted to children for "unhealthy" food across all media, including traditional (television, radio, cinema) and modern (social media, websites, apps). The food products consider "unhealthy" or "HFSS" are those identified by UK's Nutrient profiling model (Public Health England, 2018).

Results from the first evaluations of the UK intervention indicated that exposure to HFSS advertising decreased by 39% among children aged 4-9 and by 28% among children aged 10-15, as a result of marketing regulations (Ofcom, 2008). A recent WHO systematic review on food marketing policies concludes that restricting marketing may result in a reduction in food purchasing. This conclusion is drawn from four studies, one of them conducted in the UK[1]. The latter observed a reduction of HFSS expenditure per capita of £6.2 on foods and £2.7 on drinks due to a reduction in TV advertising (Silva, 2015). However, evidence on dietary intake seems to be very uncertain (WHO systematic review on the effectiveness of policies restricting marketing to children). Further, the STOP WP4 Deliverable D4.1 noted large gaps in the evidence on the effect of this intervention, especially on marketing on non-traditional media.

In the simulations, we use the effects of a decreased exposure to advertising on body weight and consumption drawn from studies looking at the impact of exposure to media on children's BMI (e.g. Boyland, 2016). Given the paucity of evidence, we use estimates based on a meta-analysis that envisaged a reduction of BMI of 0.31 kg/m2 among children aged between 5 and 18 due to limited exposure to TV advertising (Goryakin et al., 2017). This value coincides with estimates of an earlier study that calculated a reduction of children's BMI of 0.13 to 0.34 kg/m2 due to advertising restrictions (Sassi, 2010).

The eligible population is all children between 2 and 18 years of age. However, given the availability of data, it is assumed that the effect is observed from age 5 onwards. In the model, we use estimates disaggregated by age group based on calculations of a recent report of the OECD (OECD, 2019). They assume the effect on BMI follows a gradual change over time, whereby children between 5 and 12 years of age experience a reduction of 0.12 BMI (reached at age+1 and then constant until

[1] Other studies were conducted in countries outside Europe: Canada, US and Singapore.

age 12); and children between 12 and 18 experience a reduction of 0.31 BMI (reached at age+1 and then constant until age 18). Further, when children reach the age of 18, it is assumed that they have a smaller reduction of BMI, of 0.16, over one year, which remains constant over the life-course (OECD, 2019).

At this stage, the STOP model does not account for differences across social groups because there is no evidence available to feed the model with such parameters. If available, in the next deliverable we will use estimates from policy options aimed at tackling digital marketing to children and adolescents using regulations scenarios of the WHO CLICK framework.

It is assumed that the intervention will be implemented between 2020 and 2050.

3.5 Food reformulation of unhealthy food products consumed by children

Food reformulation policies have been implemented by governments since the mid-2000s to improve diet-related outcomes (Gressier et al, 20020). Evidence shows that reduction of sodium and trans-fatty acid contents in food products is linked with improvements in nutrient intake and health status (Gressier, et al 2020). Less evidence, however, has been found on the reformulation of sugar content, which can play an important role in childhood obesity prevention. France, the Netherlands, Norway and the UK have adopted sugar reduction strategies. The UK has also conducted evaluations of its strategy, which are publicly available. We will, therefore, use evidence from the sugar reduction programme of England to simulate an extension of this intervention in other EU countries. The English programme aims at reducing the overall sugar content of food products and drinks that contribute the most to children's sugar intake. The goal was to remove 20% of sugar levels to a set of food products by 2020: breakfast cereals, yogurt and fromage frais, morning goods, sweet spreads and sauces, biscuits, cakes, puddings, chocolate confectionery, sweet confectionery, ice cream, milk-based drinks, and juice-based drinks. This target was set on a voluntary scheme for the food industry. Evidence from Public Health England showed that the overall reduction was 3% in a three-year period (Public Health England, 2020). Products with the largest reductions were breakfast cereals (13.3%) and yogurt and fromage frais (12.9%). In our models, we will use these three-year results to simulate the effect of a voluntary scheme of sugar reduction levels in children's daily calorie intake. We will compare it with the 20% reduction goal assuming this level was reached under a mandatory scheme to the food industry.

3.6 Nudges in schools: food environment

Interventions using behavioural insight (BI) to improve children's diet and tackle childhood obesity are being used across settings. These interventions focus on modifying the choice architecture without changing incentives or restrictions (Chambers et al, 2020). Evidence from a STOP systematic review concluded that small changes in children's physical and social environments significantly influences children's diet-related outcomes, with educational settings being the most common and effective place for BI interventions (n=108 articles, with n=137 interventions). We will use data from the STOP systematic review on the effectiveness of school-based interventions to improve the food choice architecture of schools; that is, the aspects of the school-food environment that influence food selection: school ambience, placement, presentation, availability, and accessibility of food (Pineda et al., 2020). Estimates from a meta-analysis of this review suggest the pool effects of these interventions are associated with a reduction in BMI (standard mean difference: −0.12, 95% CI:-0.15, -0.10), and an increase in fruit consumption (+0.19 portions per day, 95% CI:0.16,0.22). This review included 100 papers with a diversity of interventions from banning food items in the school canteen and regulation on portion sizes to restriction of vending machines and guidelines. We will simulate the effect of specific interventions to provide comparisons that can shed light on the most cost-effective interventions.

3.7 School-based interventions: physical activity

The evidence to model school-based interventions promoting physical activity will be taken from the assessment on the effects of the "Healthy Lifestyle" intervention in Slovenia (STOP WP7, Deliverable D7.3); and from evidence of the STOP systematic review and meta-analysis on the effectiveness of this kind of interventions (Podnar et al., 2021). The assessment of the Slovenian intervention showed that children who were not exposed to this physical-activity intervention had 10% higher odds of experiencing obesity than children in the intervention group. Moreover, the effect of the intervention increased with longer exposure; and was no longer observed when funding to the programme stopped. We will complement this evidence with findings from the systematic review on school-based physical activity interventions. The review identified 146 studies, which were used to conduct a meta-analysis. The review provided estimates of studies that assessed three different outcomes: BMI, BMI z-scores and Body Fat. Overall, estimates suggest that fitness interventions are associated with a significant reduction in body fat (standard mean difference: −0.11, 95% CI:-0.26, -0.04). In addition, it observed less favourable effects in targeted interventions compared with more universal ones. We will use the pooled overall parameters as well as those disaggregated by socioeconomic background and type of intervention in our models.

3.8 Effect of policies on different socio-economic groups, different duration, and different policy- mix

Policymakers may want to consider whether interventions should be universal or targeted: equity reasons. It is possible that some interventions might widen or narrow the socio-economic difference in obesity risk. Therefore, when parameters are available, the model will allow estimating the effect of interventions for different socioeconomic groups. In addition, policymakers may want to examine the difference between interventions of short-term duration versus those of longer exposures. Hence, the model will allow simulating the effect of different durations of interventions. Lastly, the model will allow comparing the effect of policies when implemented in insolation and the effect of policies implemented in combination. The latter simulation will require several assumptions on the complementarity and substitution effects of the policies under study. We will base such assumptions on studies that have examined such issues.

4 Outcome measures

The STOP microsimulation produces detailed projections of the simulated population over time providing granular estimates at an individual level. These outputs are then aggregated to produce various relevant metrics for policy analysis, by targeting one of the following dimensions: demographics, risk factors, and diseases.

4.1 Demographics

The analysis will focus on understanding the effects that health policies and interventions play on increasing life expectancies. The analysis will be performed for each year within the projection period to fully understand the magnitude and time trend gains that could be expected from various policies. Additional analyses based on gender and socioeconomic status such as education and income levels will be carried out to draw a complete picture of the potential impact that implemented health policies can have on individuals from different socio-economic groups.

4.2 Risk factors

Simulated policies and interventions will target, either directly or indirectly, physical activity, diet, energy intake, and body mass index (BMI). The model will produce thorough tables and graphs of the prevalence and progression of each one of these risk factors within the population by age, gender, and socio-economic status. A comparative analysis with the baseline scenario will be carried out to quantify the magnitude of changes in these risk factors that is attributable to the policy. The analysis will focus mainly on changes in obesity prevalence within the population in general and children, in particular.

4.3 Burden of diseases

Heath policies have an indirect effect on diseases through modifiable risk factors such as diet and physical activity. The aim of these analyses is to assess the benefits of health policies in improving overall population wellbeing by reducing disease prevalence and mortality. The following metrics are used for this purpose:

- **Disease prevalence:** changes in the underlying risk factors such as diet, physical activity, and obesity will lead to changes in disease prevalence. The model will produce projections of disease prevalence for each year of the simulation to visualise the speed at which health policies impact diseases. The analysis will be carried out by age, gender and socio-economic status for the same reasons explained previously.

- **Disability-adjusted life years (DALYs):** the model combines years of life lost due to premature mortality (YLLs) and years of healthy life lost due to disability (YLDs) to assess the overall burden of diseases.

- **Health Care Expenditure:** the model uses advanced machine learning algorithms to calculate the overall treatment costs under different scenarios. Most importantly, the model accounts for the effect that comorbidities have on treatment costs.

5 Software Implementation

The STOP microsimulation (Health GPS), described by the STOP D9.2 report, is being developed in collaboration between the Centre for Health Economics & Policy Innovation (CHEPI), Imperial College London; and INRAE, France. The software architecture adopts a modular design approach to provide the building blocks necessary to compose the microsimulation, which is written in modern, standard ANSI C++, targeting the C++20 version and using object-oriented principles for software development. The software application is open source[2] and contains four main components:

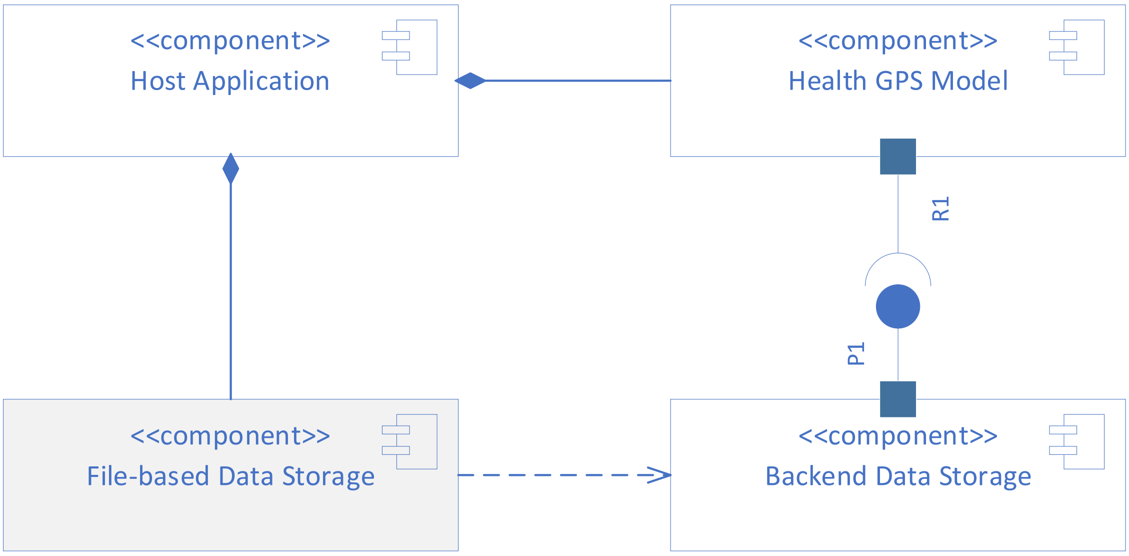


Figure 1 - STOP Microsimulation Components

- ***Health GPS Model* -** defines the microsimulation executive, core modules and algorithms used to create the virtual population, simulate over time, and produce results.
- ***Host Application*** - responsible for parsing the user's inputs via a configuration file, initialise the supporting infrastructure, compose the Health GPS instance by assembling the required modules, running the experiment, and collect the results. This component is provided as a console terminal application, but can equality be a graphical user interface (GUI) or web page.
- ***Backend Data Storage*** - provides an interface (Data API) and persistence-agnostic data types (plain old class object - POCO) are required to create the internal modules. This component is a contract for all concrete implementations that manage the storage and access of datasets.
- ***File-base Data Storage*** - implements the Data API interface to provide a file-based storage for the modules required data. This component can be replaced by a different storage type, e.g., database, without affecting the Health GPS Model ecosystem.

These components along with the physical data storage are the minimum package to deploy and use the STOP microsimulation. All input data processing, model parameters fitting, and results analysis procedures are carried out outside the microsimulation model using tools such R and Python which are very efficient in statistical analysis and machine learning algorithms.

[2] https://imperialchepi.github.io/healthgps

5.1 Using the microsimulation

The STOP microsimulation is a data driven modelling framework, combining many disconnected data sources to support the various interacting modules during a typical simulation experiment run as described above. The framework provides a pre-populated backend data storage to minimise the learning curve for simple use cases, however advance users are likely to need a more in-depth knowledge of the full workflows. A high-level representation of the microsimulation user workflow is shown below, it is crucial for users to have a good appreciation for the general dataflows and processes to better design experiments, configure the tool to run, and quantify the results.

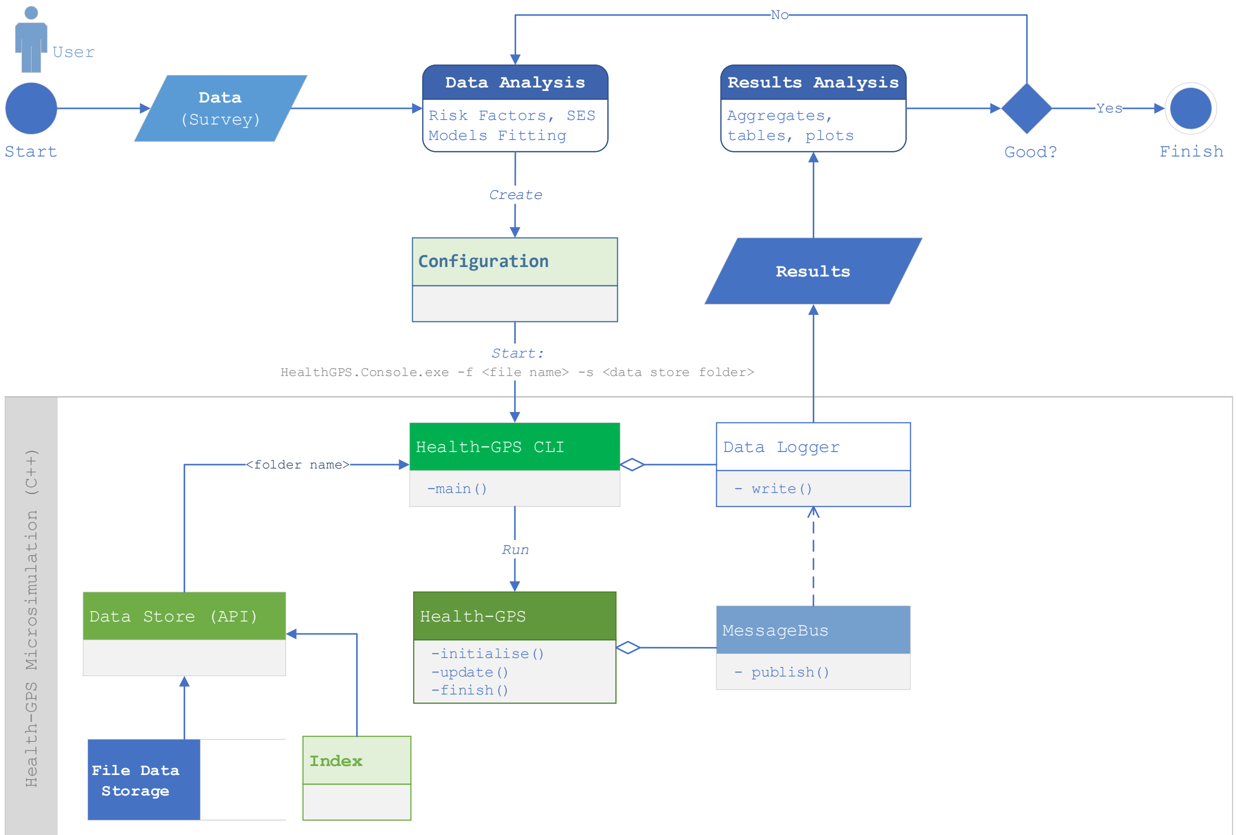


Figure 2 – STOP Microsimulation user workflow

As with any simulation model, it is the user's responsibility to process and analyse input data, define model's hierarchy, and fit parameters to data. A configuration file (JSON) is used control the simulation running settings and map the Health-GPS expected parameters to the user input data and fitted values. To get started using the microsimulation, download the latest release version from the project's website, unzip into a local folder, e.g., *C:\HealthGPS;* and run the following command on a windows terminal:

```
C:\HealthGPS> .\HealthGPS.Console.exe -f ".\example\demo.json" -s ".\data"
```

The parameter *-f* gives the configuration file full name and -*s* the path to the root folder of the file-base backend storage respectively, the website provides further information. The default output folder is *C:\HealthGPS\Result*, but this can be changed in the configuration file (demo.json).

As with the input data, it is the user's responsibility to and analyse and quantify the model results, which are saved to a chosen output folder in JSON (JavaScript Object Notation) format, an open standard file format designed for data interchange in human-readable text. All major data science tools and programming languages have libraries and functions to read/write JSON structures. To read the model results in R, for example, use the *jsonlite* package as follows:

```
require(jsonlite)
data <- fromJSON(result_filename)
View(data)
```

The above script reads the results data from file and makes the *data* variable available in R for analysis as shown below, it is equally easy to write a R structure to a JSON string or file.

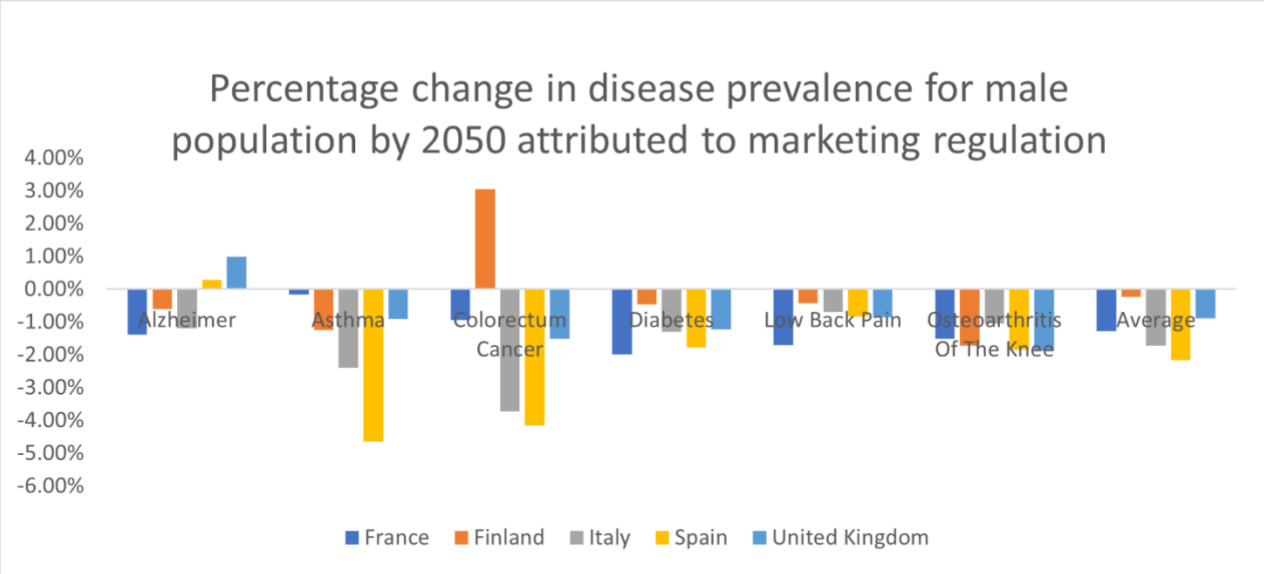
Name	Type	Value
data	list [2]	List of length 2
experiment	list [3]	List of length 3
model	character [1]	'Health-GPS'
version	character [1]	'1.0.0.0'
time_of_day	character [1]	'2021-11-07 17:14:39.2241966 GMT'
result	list [164 x 10] (S3: data.frame)	A data.frame with 164 rows and 10 columns
id	integer [164]	2 2 2 2 2 2 ...
source	character [164]	'baseline' 'intervention' 'baseline' 'intervention' 'baseline' 'intervention' ...
run	integer [164]	1 1 1 1 1 1 ...
time	integer [164]	2010 2010 2011 2011 2012 2012 ...
population	list [164 x 4] (S3: data.frame)	A data.frame with 164 rows and 4 columns
average_age	list [164 x 2] (S3: data.frame)	A data.frame with 164 rows and 2 columns
indicators	list [164 x 3] (S3: data.frame)	A data.frame with 164 rows and 3 columns
risk_factors_average	list [164 x 6] (S3: data.frame)	A data.frame with 164 rows and 6 columns
disease_prevalence	list [164 x 2] (S3: data.frame)	A data.frame with 164 rows and 2 columns
metrics	list [164 x 3] (S3: data.frame)	A data.frame with 164 rows and 3 columns

Figure 3 - Example Model Results view using R tool

The results file contains the output of all simulations in the experiment, baseline, and intervention scenarios over one or more runs. The user should not assume data order during analysis of intervention scenarios, the results are published by both simulations running in parallel asynchronously via messages, the order in which the messages arrive at the destination queue, before being written to file is not guaranteed. The robust method to tabulate the results shown above is to always group the data by *data.result(source, time)*, to ensure that analysis algorithms work for both types of simulation experiments.

6 Results: effects of interventions on health outcomes

In this section, we present estimates on the effect of interventions on a set of outcomes to illustrate how the model runs. Figure 4 presents the effect of the intervention of restricting the marketing (described in 3.4) of food products to children by comparing the trend of outcomes between 2020 and 2050 with and without intervention (baseline scenario). The results are presented for five European countries: Finland, France, Italy, Spain, and the United Kingdom. We observe that the implementation of this policy reduces the prevalence of diseases in all countries, for both men and women. Two diseases show unexpected effects: Alzheimer and colorectal cancer. This is likely to do with the small prevalence of these diseases, which makes our simulations somewhat erratic. The effect is relatively small, with a reduction of around 1 to 2 percentage points.



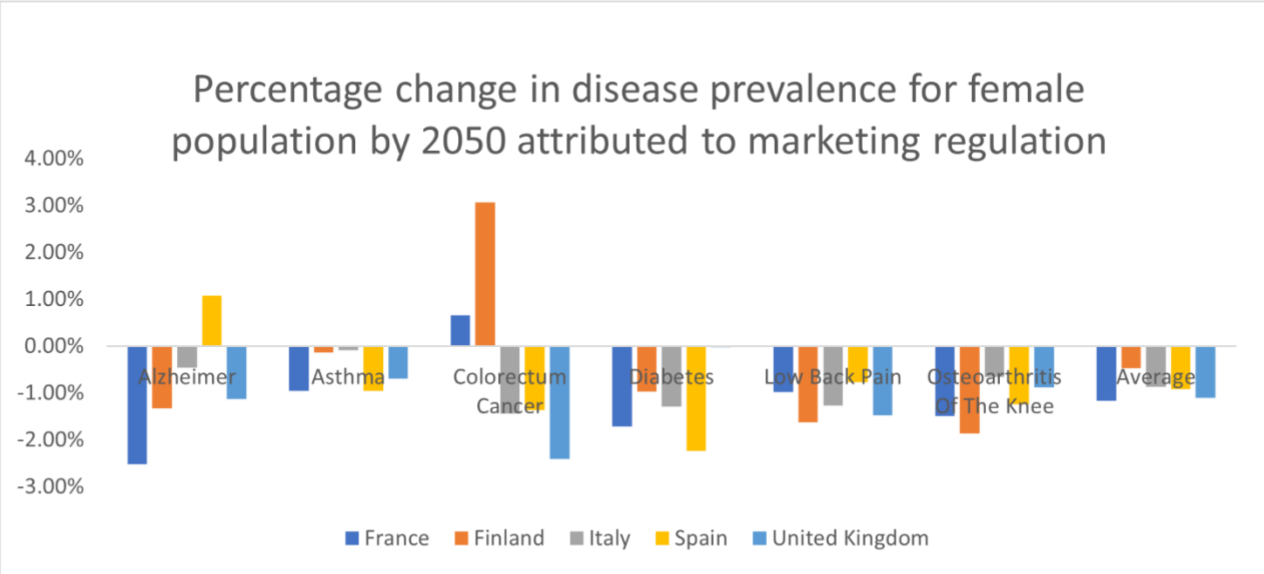


Figure 4 – Effect of marketing regulations on food to children on prevalence of diseases

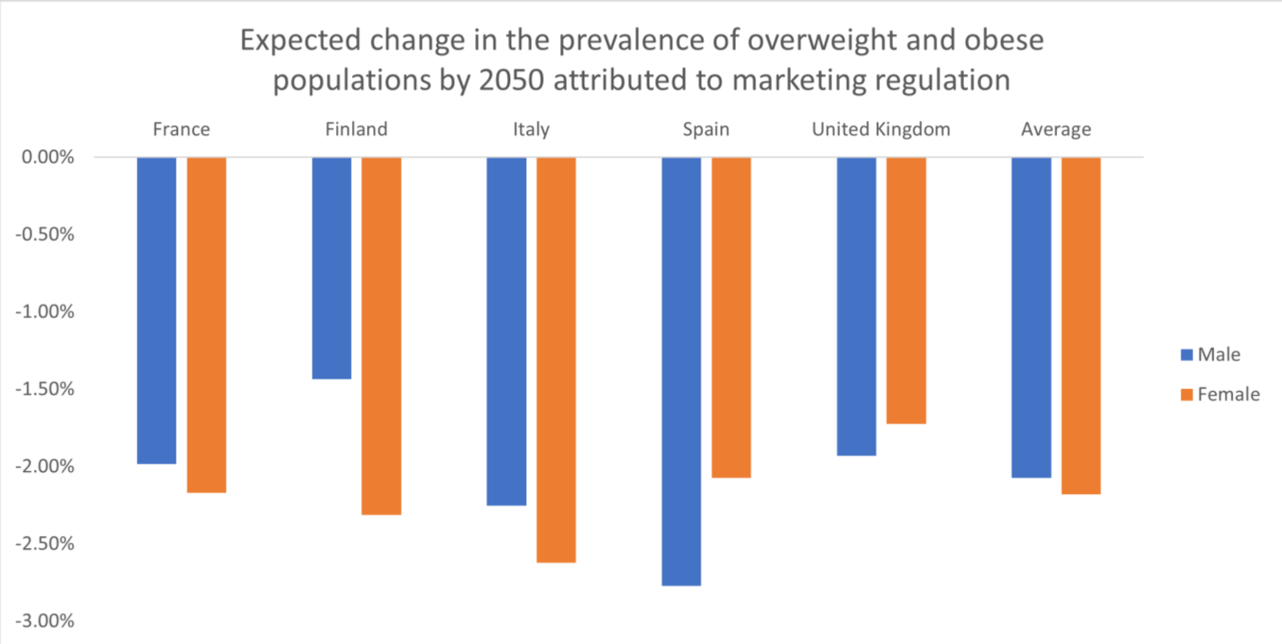


Figure 5 – Effect of marketing regulations on prevalence of overweight and obesity, by sex

Figure 5 shows the effect of implementing marketing regulations on the prevalence of overweight and obesity in the five countries examined. Compared with the baseline scenario, the share of individuals with excess weight reduces by around 2 percentage points. The effect seems to be similar for men and women, except in Finland and Spain, where males seem to benefit more from this policy. Differences across countries are relatively small so it is not clear which country would benefit most from reducing the prevalence of excess weight from this intervention. If anything, it seems that the prevalence would reduce the most among Spanish men (-2.7 percentage points); and the least among Finnish men (-1.4 percentage points).

The Annex includes estimates of the effects on the different health outcomes between 2020, the beginning of the implementation, and 2050. It is possible to observe the reduction in prevalence for each disease during the period examined.

1 Limitations

Despite the complexity of the STOP microsimulation framework, it is still based on several mathematical and epidemiological assumptions that could influence the quality of the outputs. For example:

- We assumed that risk factors are the only drivers of disease incidence and prevalence in a population. The reality is that disease acquisition and remission in real life are determined by both endogenous and exogenous factors to the individual. For example, advancements in healthcare such as the discovery of a new medication could reduce or eradicate a disease from a population. In this framework, we modelled interactions that are corroborated by robust scientific evidence, and which could be changed through health interventions and policies.
- The convergence rates of diseases and risk factors in the simulation depend on their initial prevalence. A medium/high prevalence disease such as diabetes or low back pain converges quickly whilst a low prevalence disease such as colorectum cancer requires more time.

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Similarly, YLD converges quickly as it uses the whole population for the calculation whilst YLL uses deaths only and therefore converges slowly. Therefore, running large simulations, which require both time and powerful machines, is a necessity to ensure the convergence of all outcomes.

- The framework relies on several parameters to run. Their values are calibrated using available historical data. Therefore, it is paramount to analyse the sensitivity of outcomes to each one of the parameters to ensure robust findings.
- For some of the studied policies, there is only cross-sectional data about their effectiveness and not enough evidence on the long-term effect of these interventions. Hence, we made some assumptions on how the effect would evolve over time. Although we made these assumptions, our main objective was to ensure a smooth transition between the different age groups.
- Limited evidence on the effect of interventions by socioeconomic characteristics do not allow us to feed the model with this type of information. Hence, we need to assume that the effect is similar across groups. However, even if we do not have evidence of different responses by SES groups, the model still calculates effects on different SES groups, which will be different because of their different exposures and characteristics, so it is still possible to examine different impacts in different SES groups even assuming that the intervention has the same effect on everyone.

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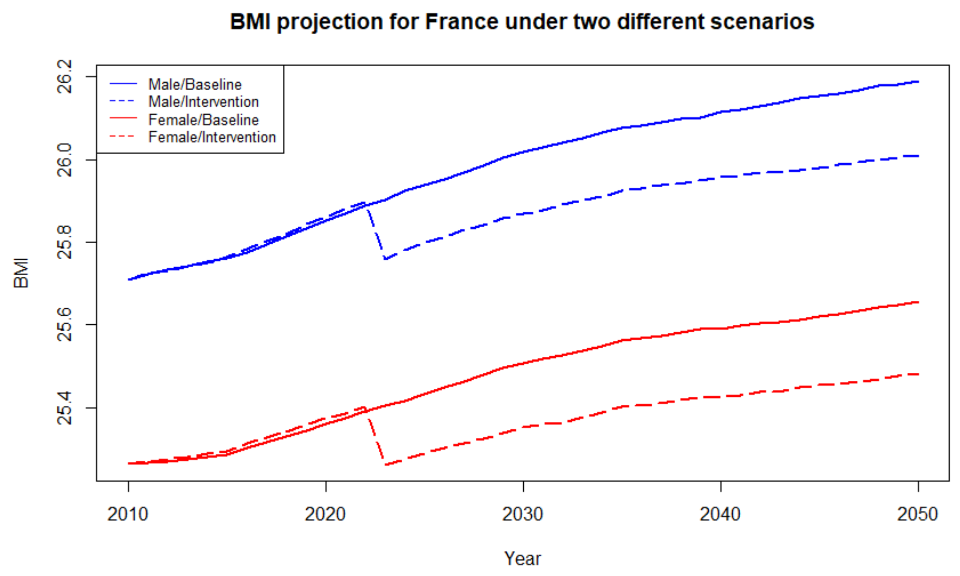
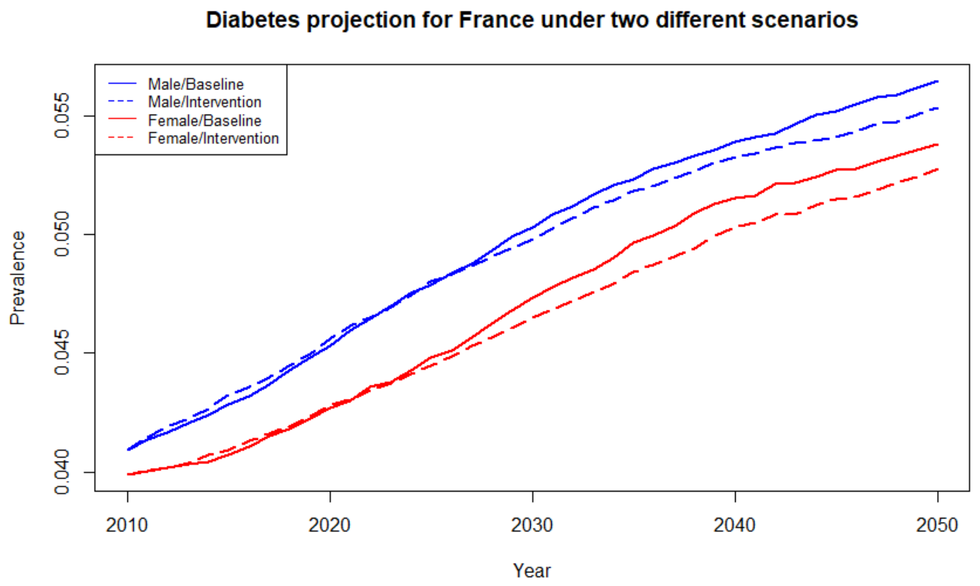
Annex

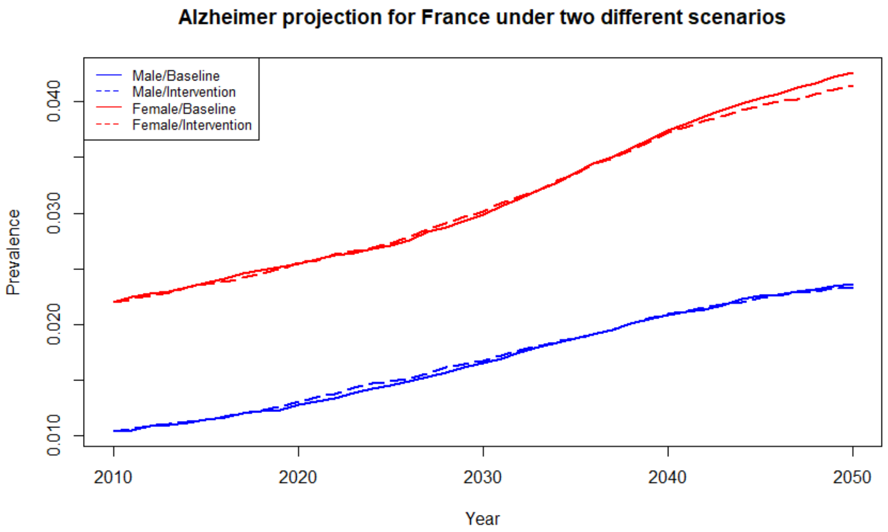
This section presents results on the effect of interventions for a number of health outcomes of the five countries presented in the report.

A.1 Effect of marketing regulations of food products to children on health outcomes

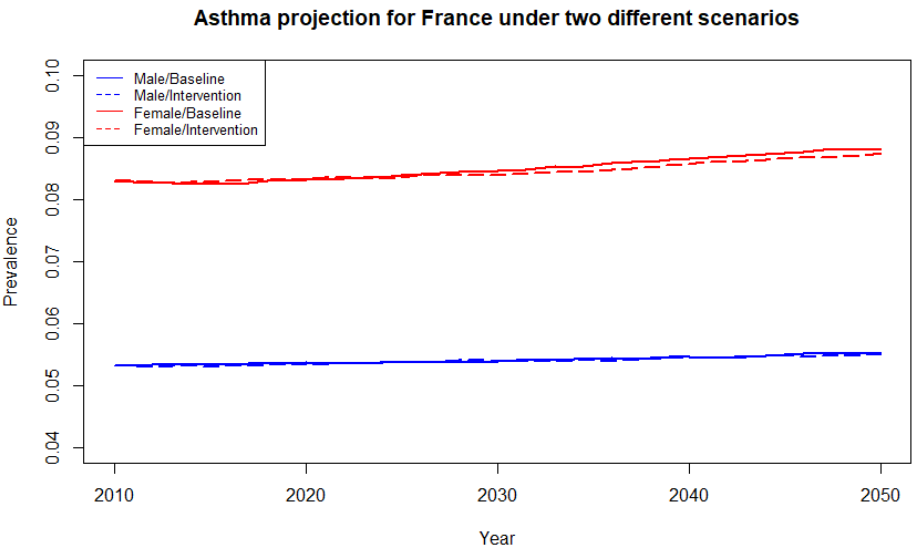
France



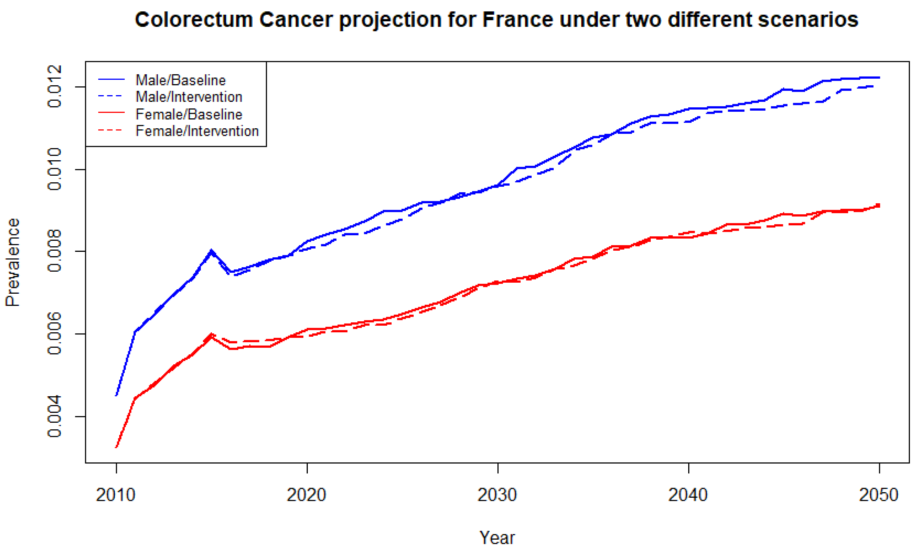




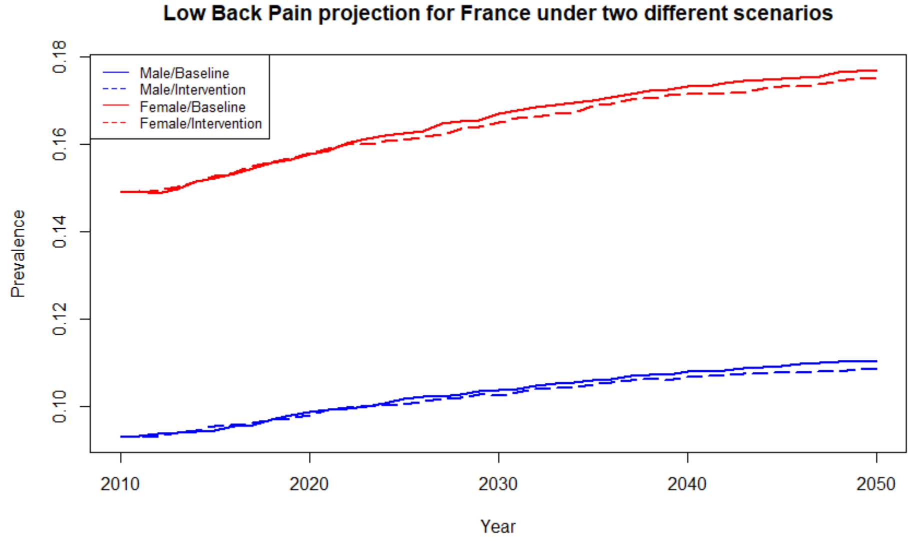
Alzheimer projection for France under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
Prevalence
0.010
0.020
0.030
0.040
2010
2020
2030
2040
2050
Year

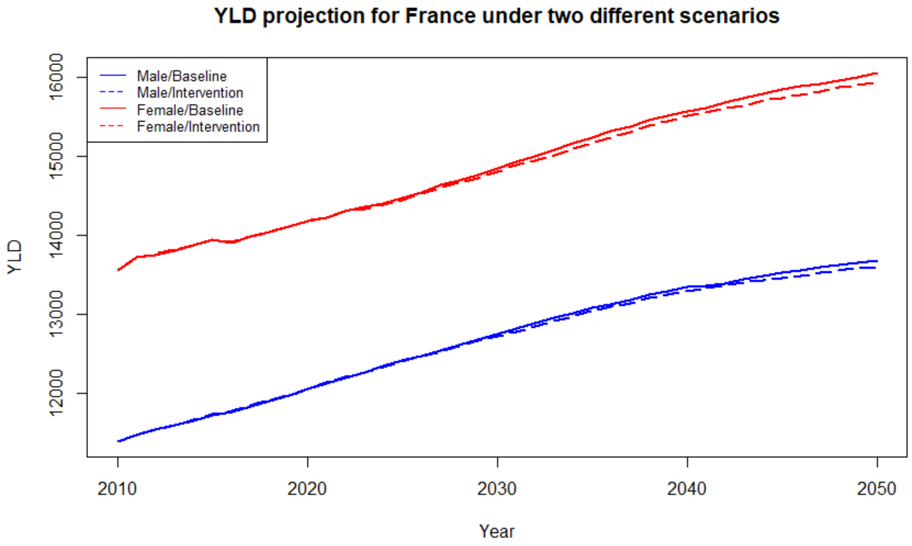


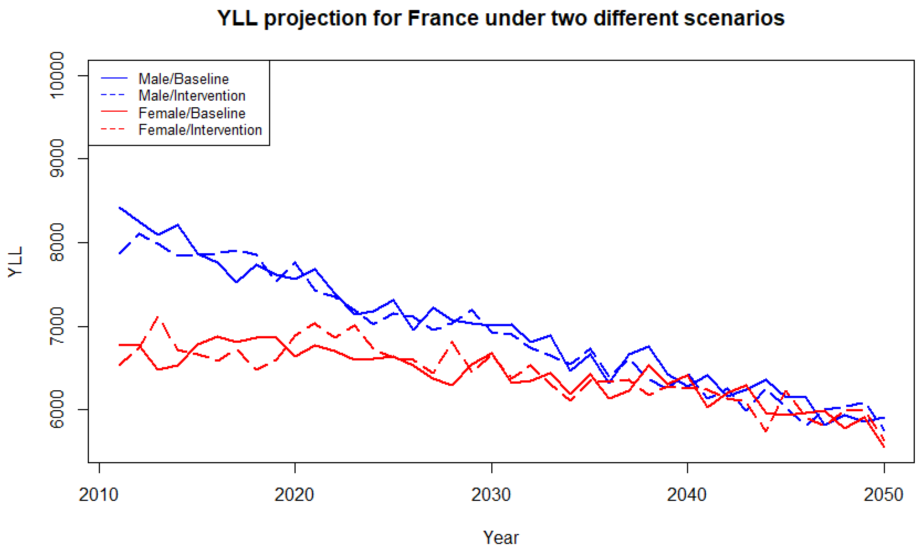
Asthma projection for France under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
Prevalence
0.04
0.05
0.06
0.07
0.08
0.09
0.10
2010
2020
2030
2040
2050
Year

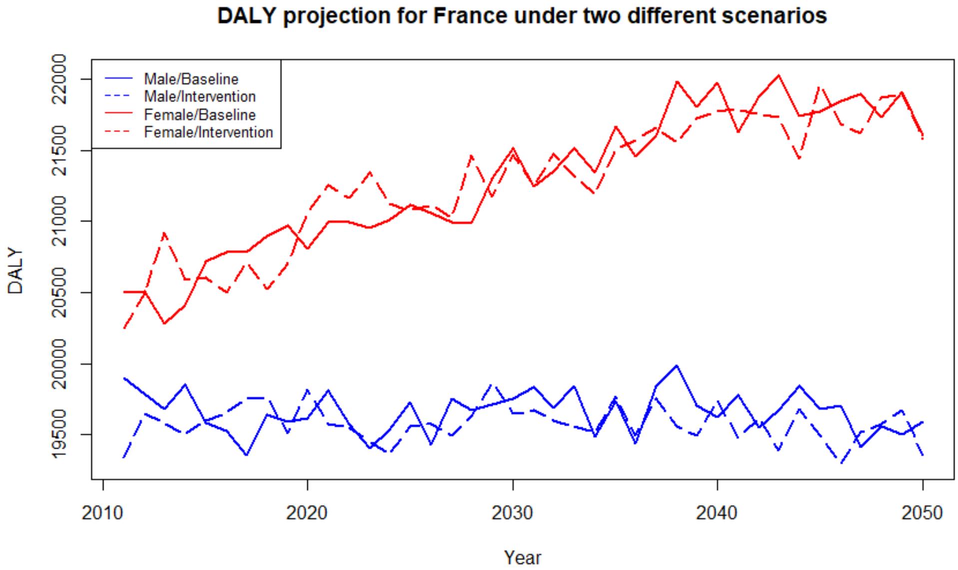


Colorectum Cancer projection for France under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
Prevalence
0.004
0.006
0.008
0.010
0.012
2010
2020
2030
2040
2050
Year


Low Back Pain projection for France under two different scenarios
Prevalence
0.10
0.12
0.14
0.16
0.18
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
2010
2020
2030
2040
2050
Year

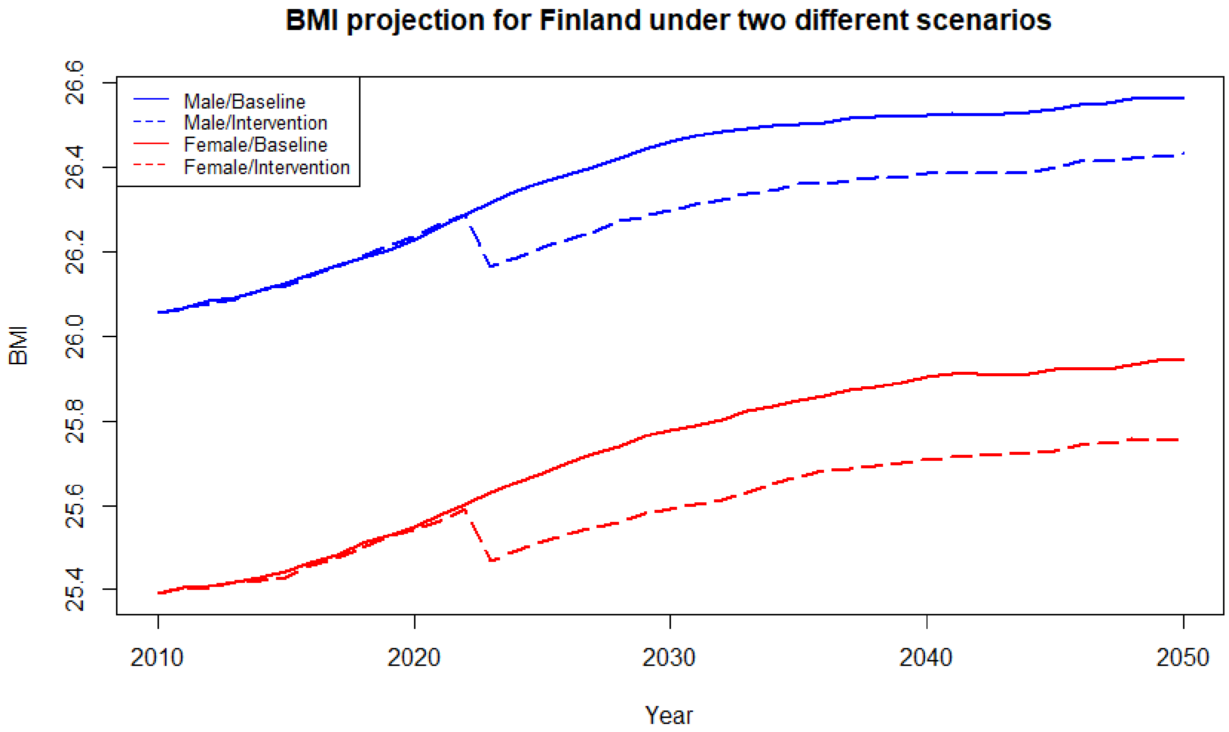

YLD projection for France under two different scenarios
YLD
12000
13000
14000
15000
16000
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
2010
2020
2030
2040
2050
Year


YLL projection for France under two different scenarios
YLL
6000
7000
8000
9000
10000
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
2010
2020
2030
2040
2050
Year

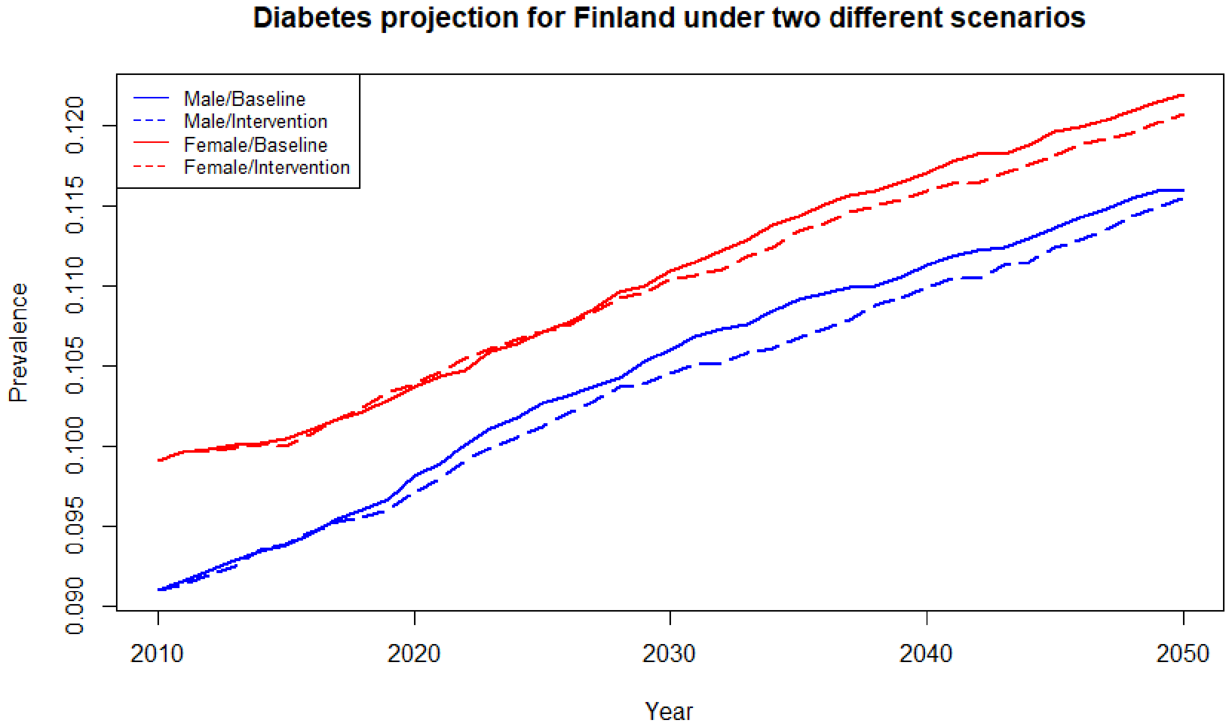


DALY projection for France under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
DALY
19500
20000
20500
21000
21500
22000
2010
2020
2030
2040
2050
Year

Finland

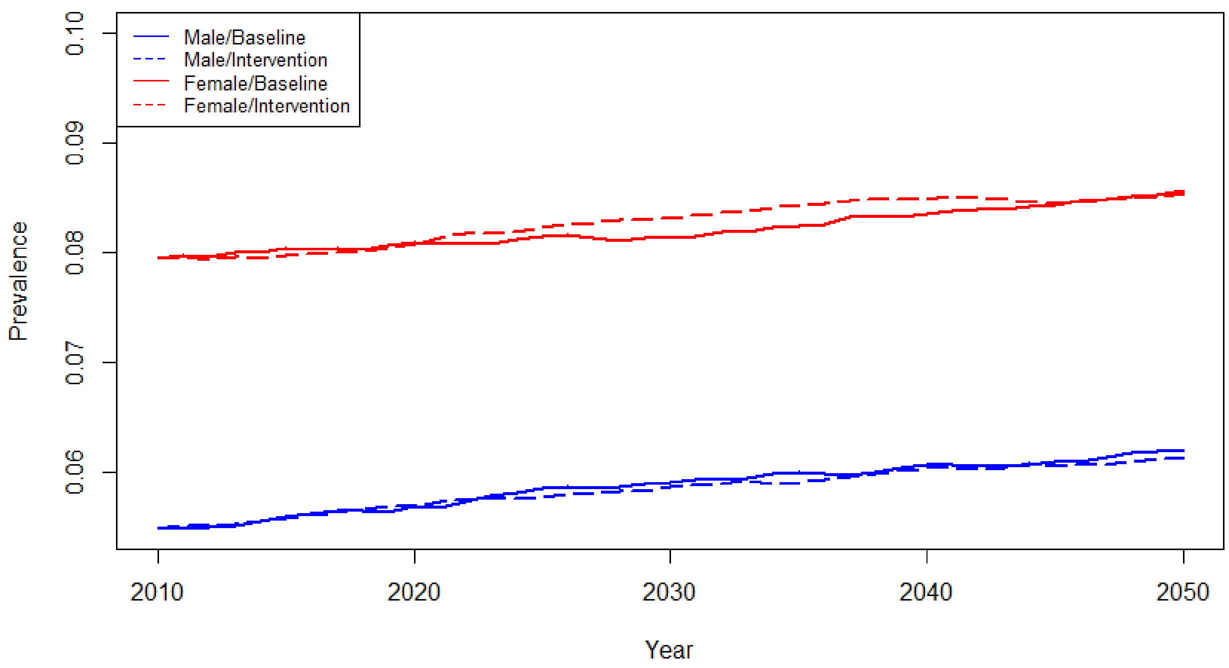


BMI projection for Finland under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
BMI
26.6
26.4
26.2
26.0
25.8
25.6
25.4
2010
2020
2030
2040
2050
Year

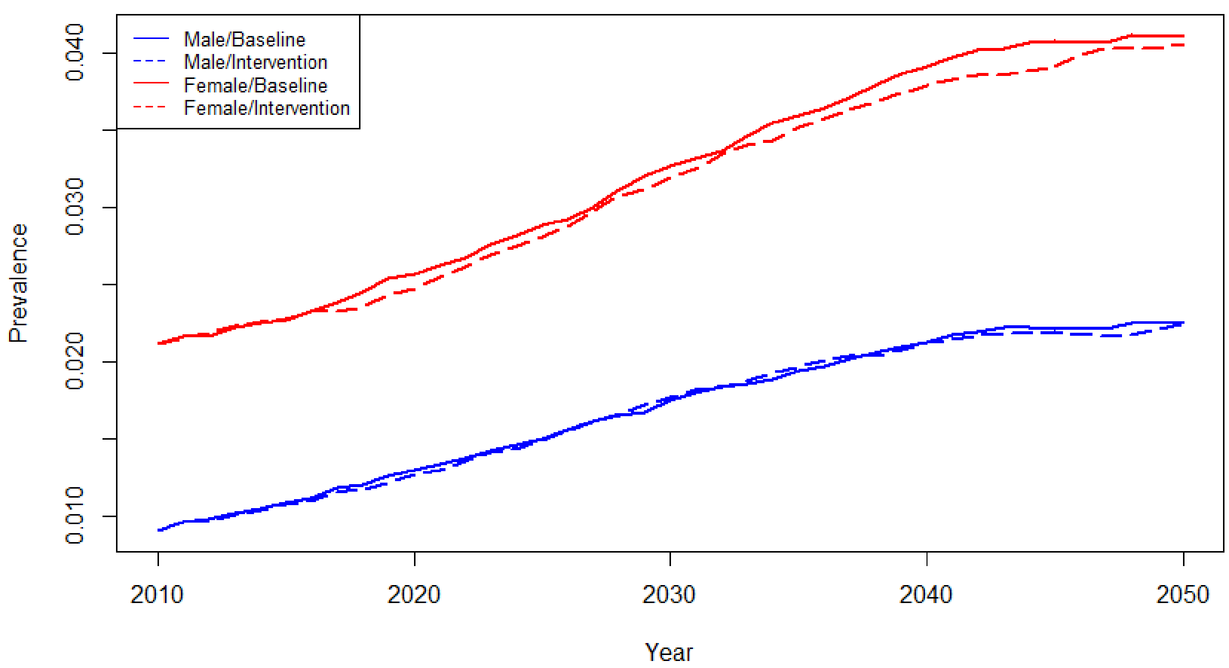


Diabetes projection for Finland under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
Prevalence
0.120
0.115
0.110
0.105
0.100
0.095
0.090
2010
2020
2030
2040
2050
Year

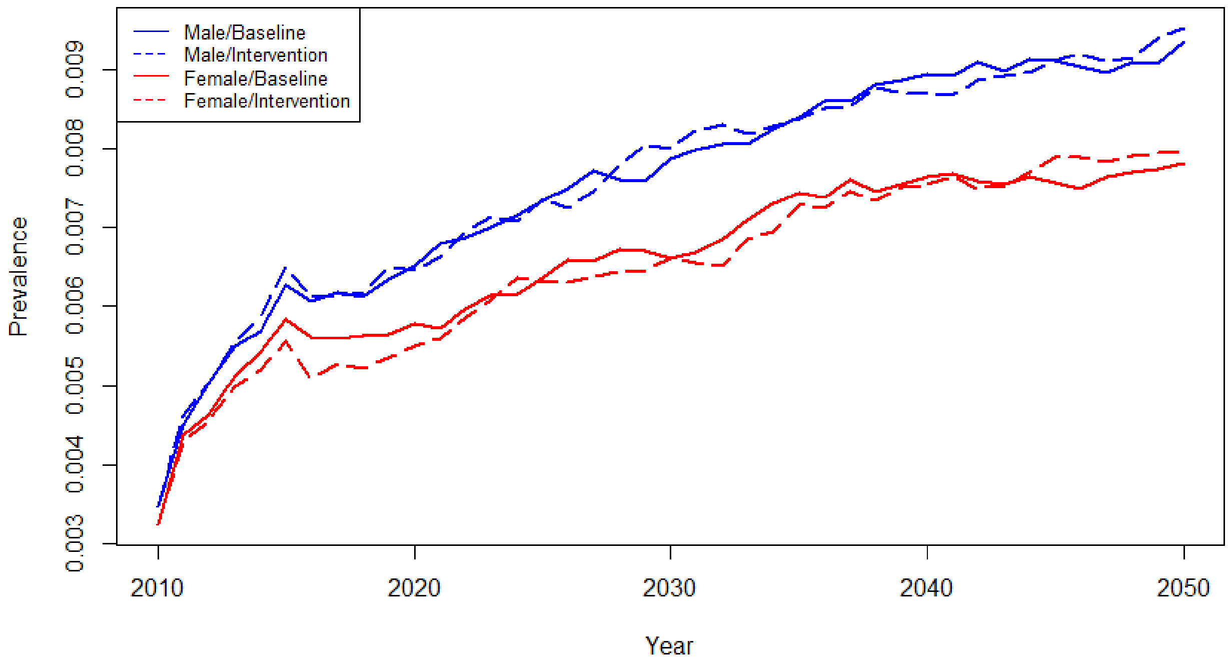
Asthma projection for Finland under two different scenarios



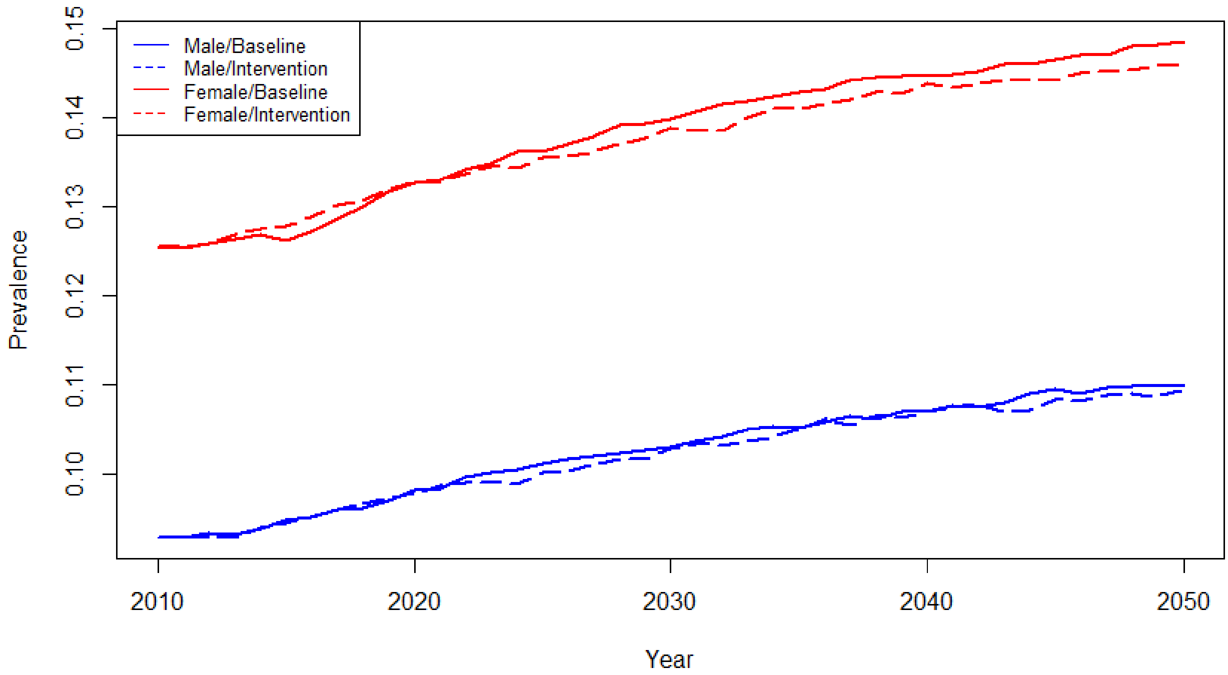
Alzheimer projection for Finland under two different scenarios

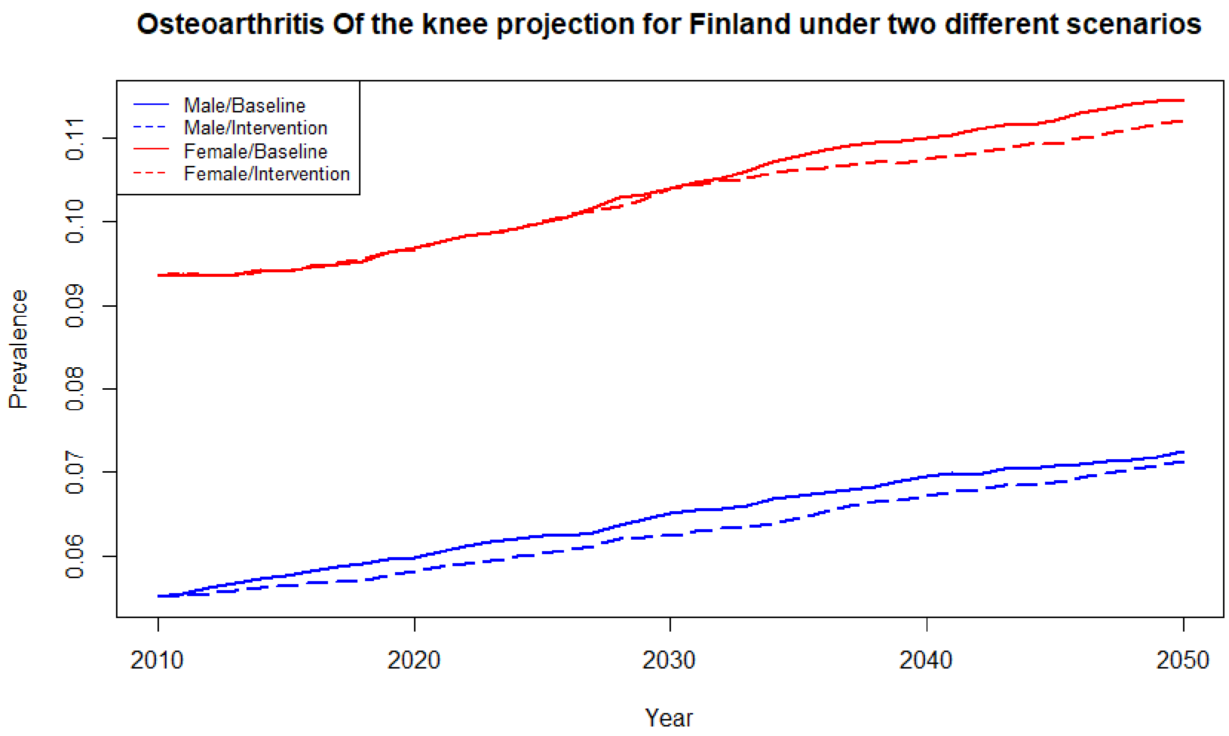


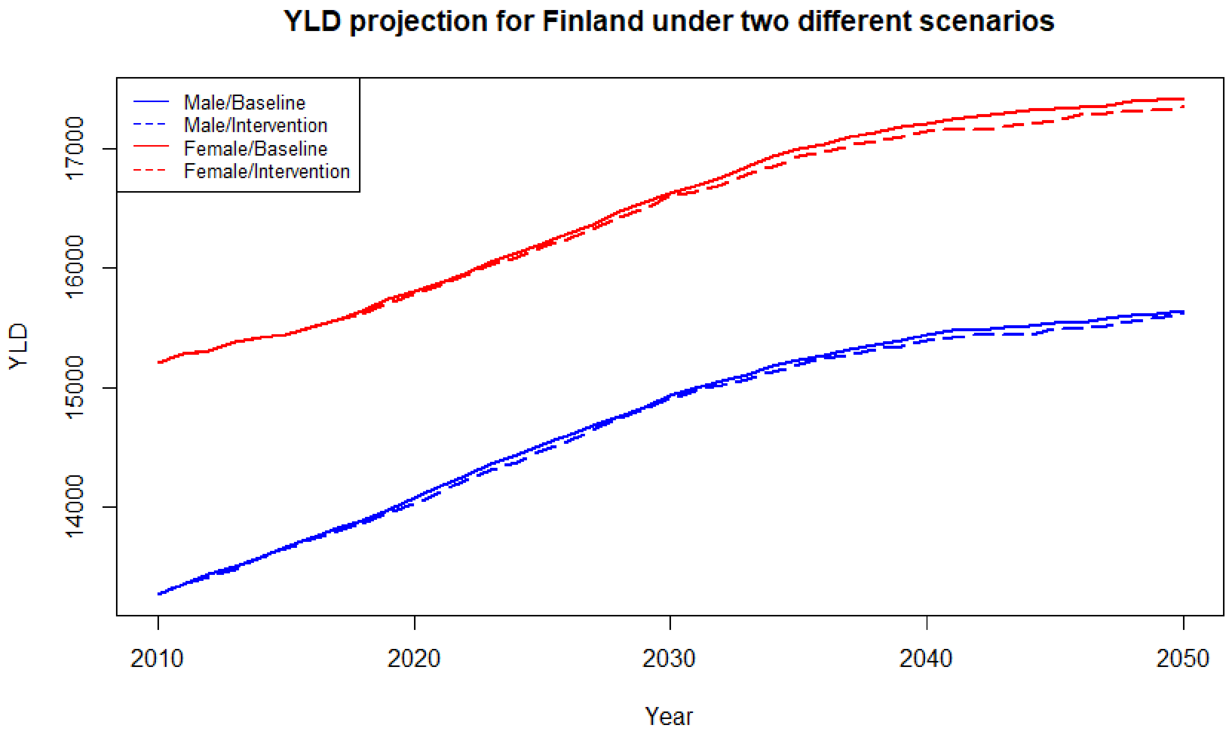
Colorectum Cancer projection for Finland under two different scenarios



Low Back Pain projection for Finland under two different scenarios




Osteoarthritis Of the knee projection for Finland under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
Prevalence
0.06
0.07
0.08
0.09
0.10
0.11
2010
2020
2030
2040
2050
Year


YLD projection for Finland under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
YLD
14000
15000
16000
17000
2010
2020
2030
2040
2050
Year

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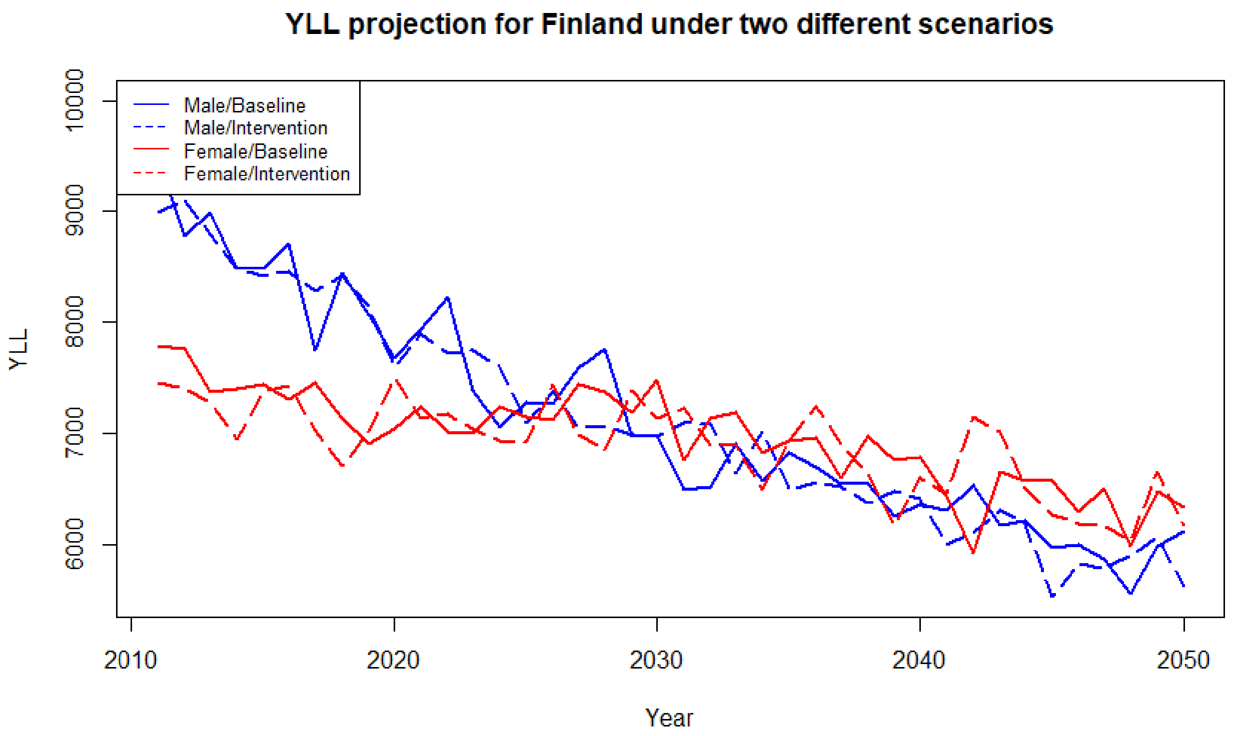
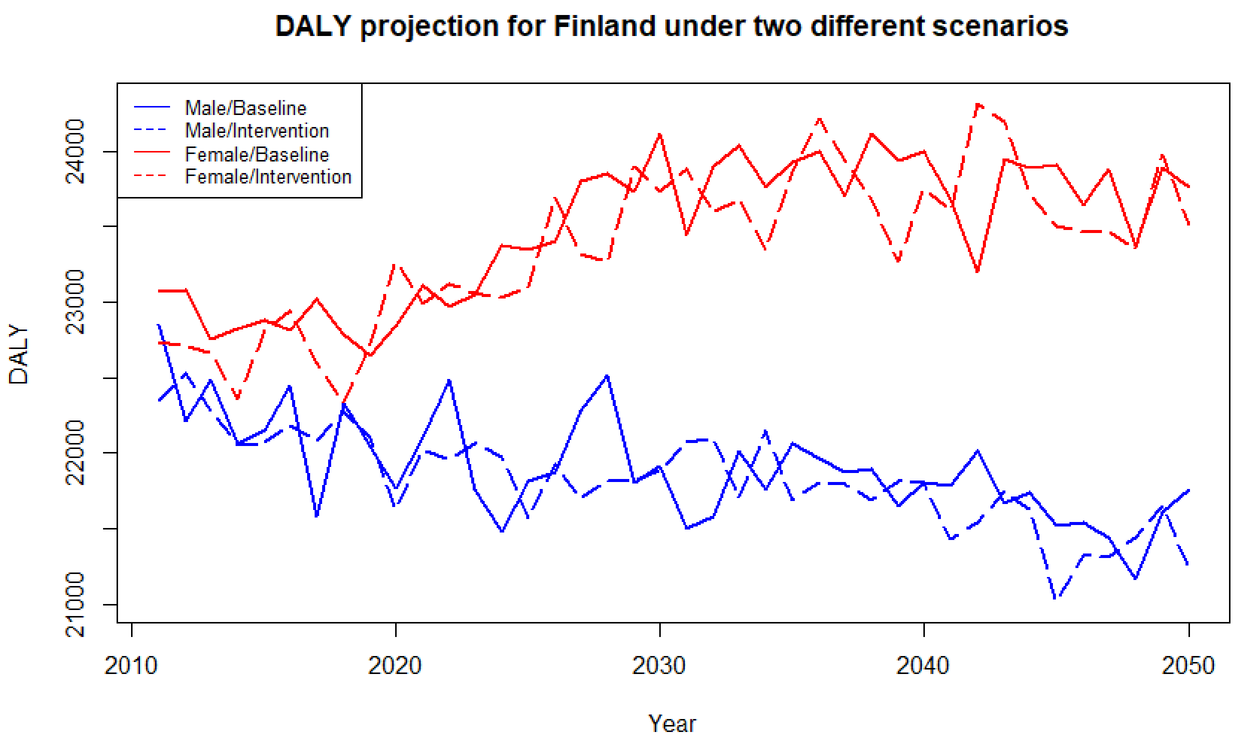
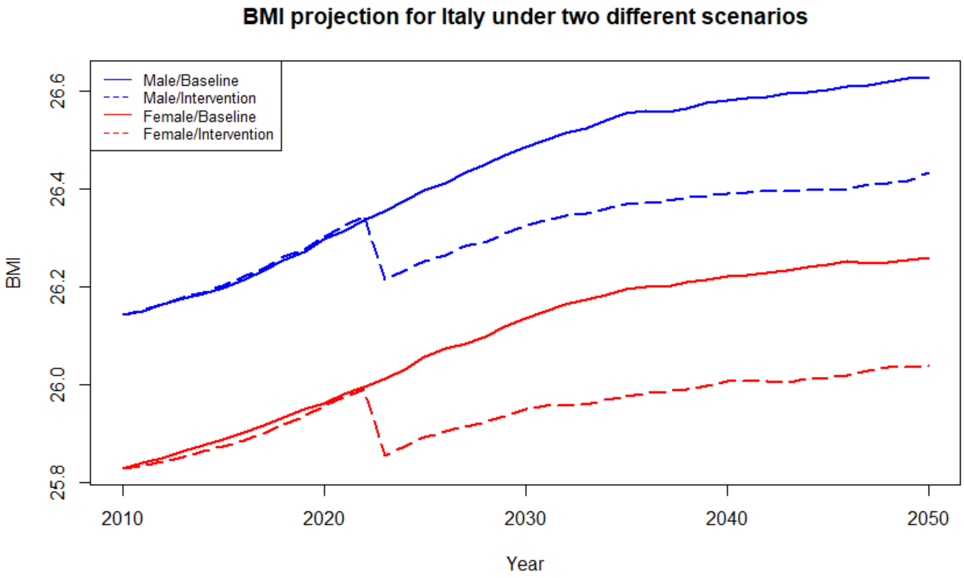
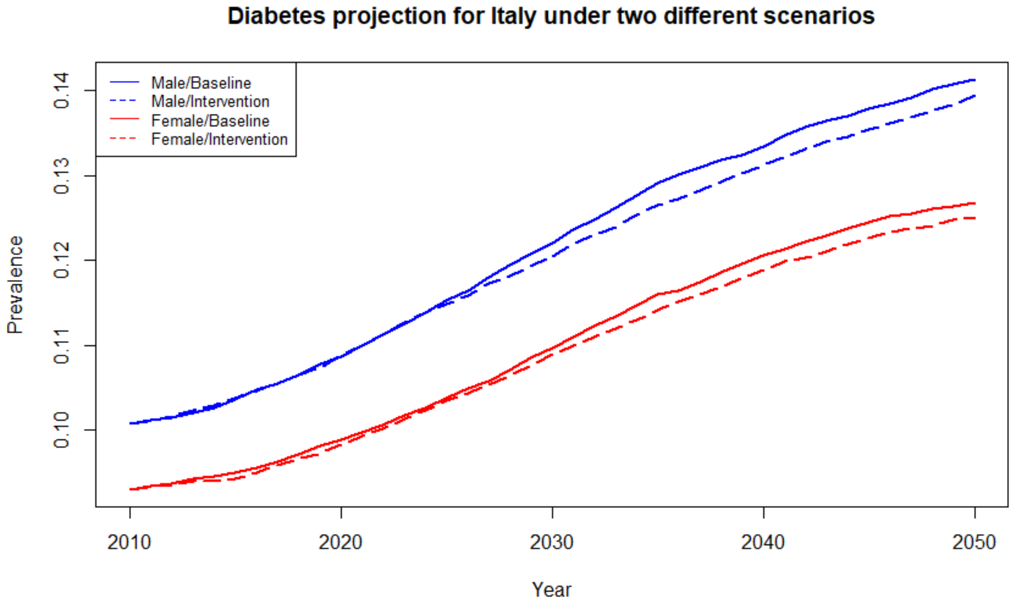
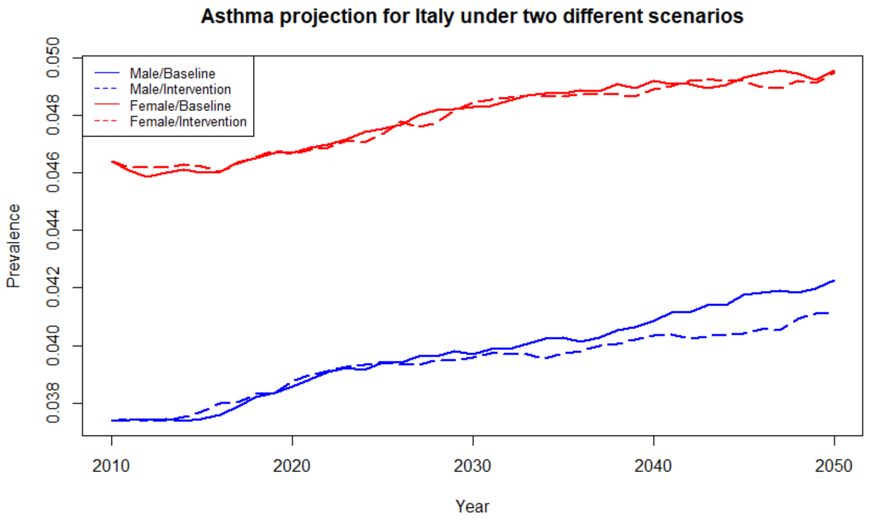


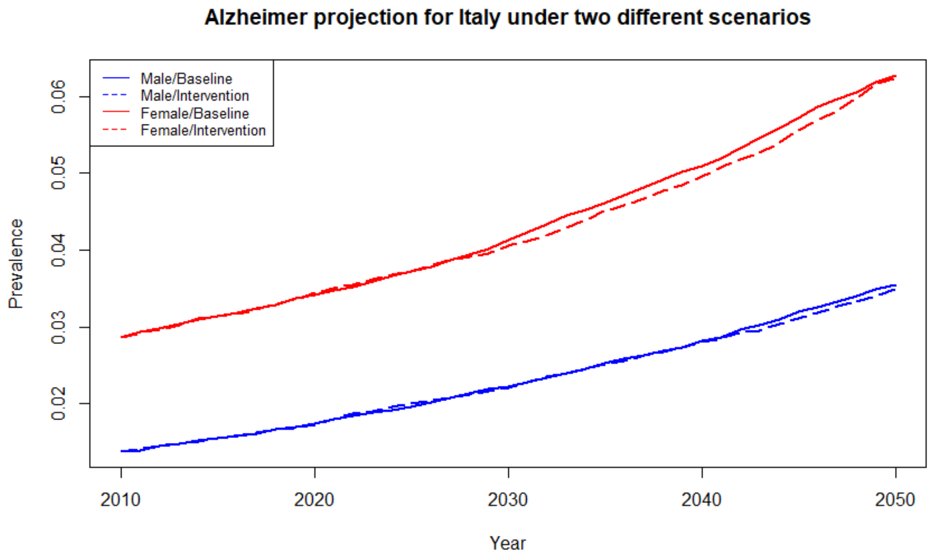


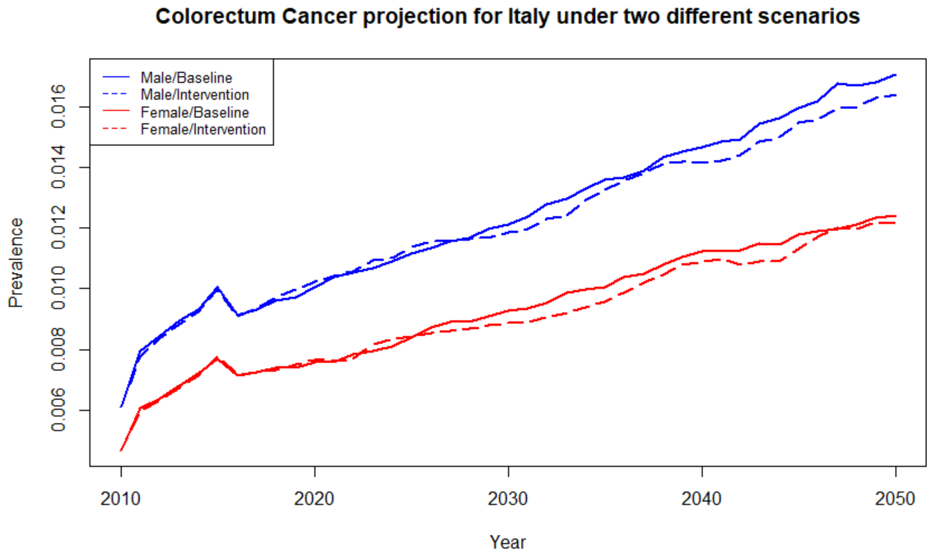
Italy


BMI projection for Italy under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
BMI
26.6
26.4
26.2
26.0
25.8
2010
2020
2030
2040
2050
Year

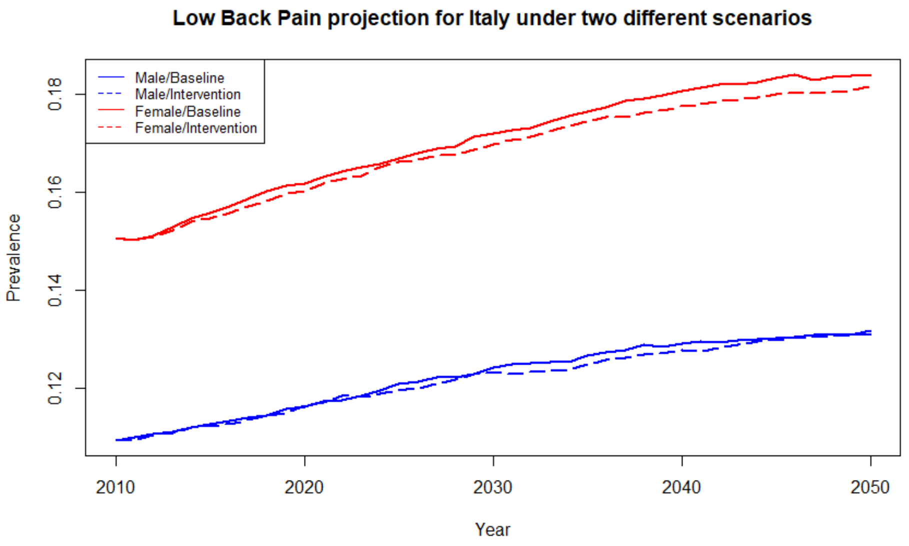

Diabetes projection for Italy under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
Prevalence
0.14
0.13
0.12
0.11
0.10
2010
2020
2030
2040
2050
Year

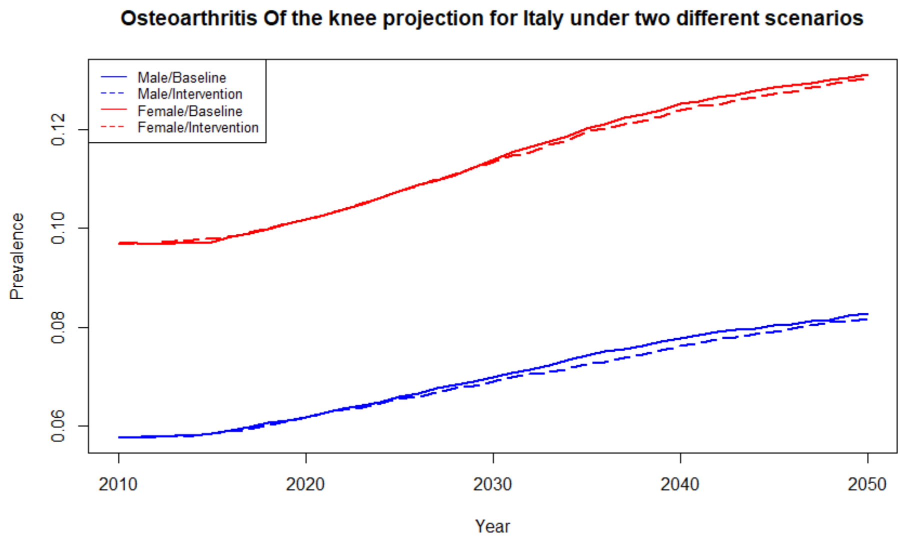

Asthma projection for Italy under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
Prevalence
0.038
0.040
0.042
0.044
0.046
0.048
0.050
2010
2020
2030
2040
2050
Year

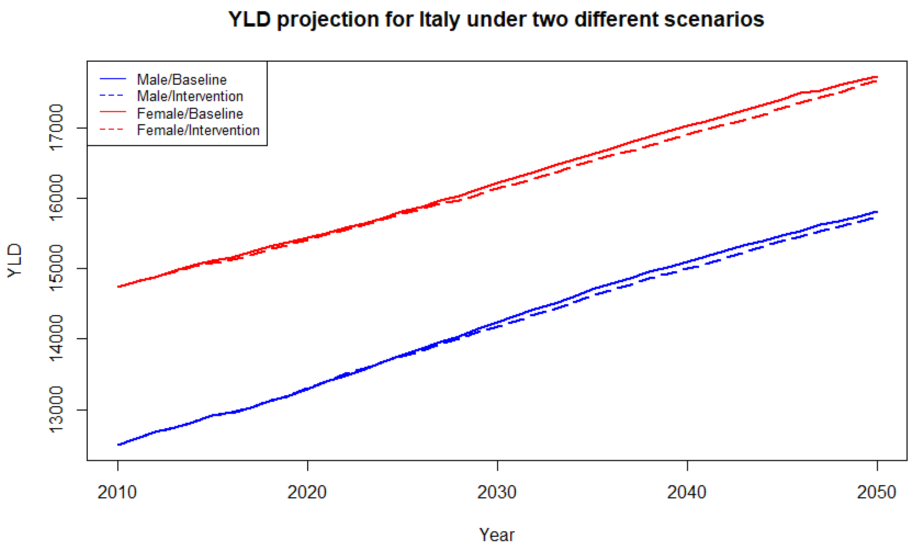

Alzheimer projection for Italy under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
Prevalence
0.02
0.03
0.04
0.05
0.06
2010
2020
2030
2040
2050
Year


Colorectum Cancer projection for Italy under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
Prevalence
0.006
0.008
0.010
0.012
0.014
0.016
2010
2020
2030
2040
2050
Year

Science and Technology in childhood Obesity Policy







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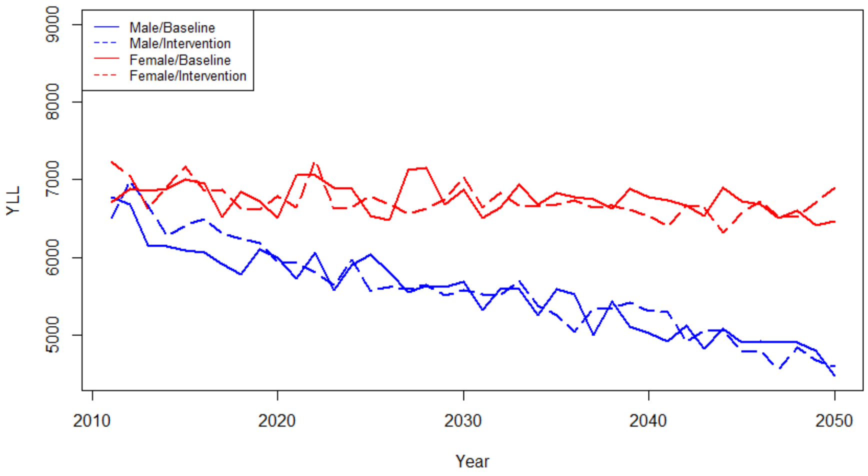
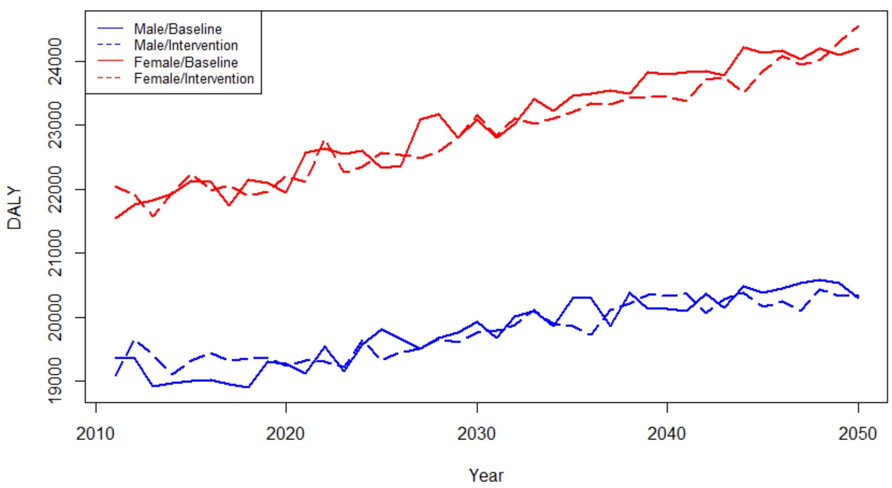
YLL projection for Italy under two different scenarios



DALY projection for Italy under two different scenarios



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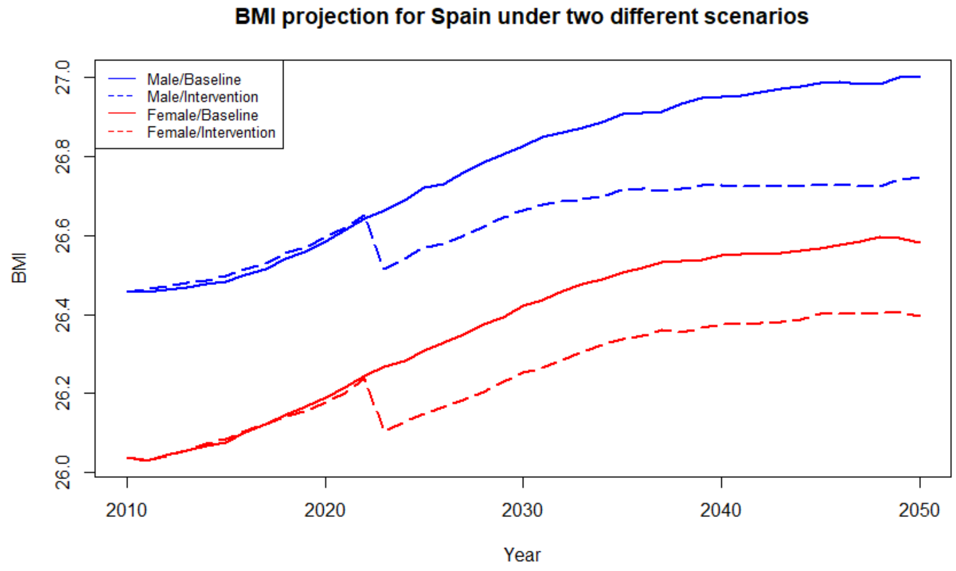
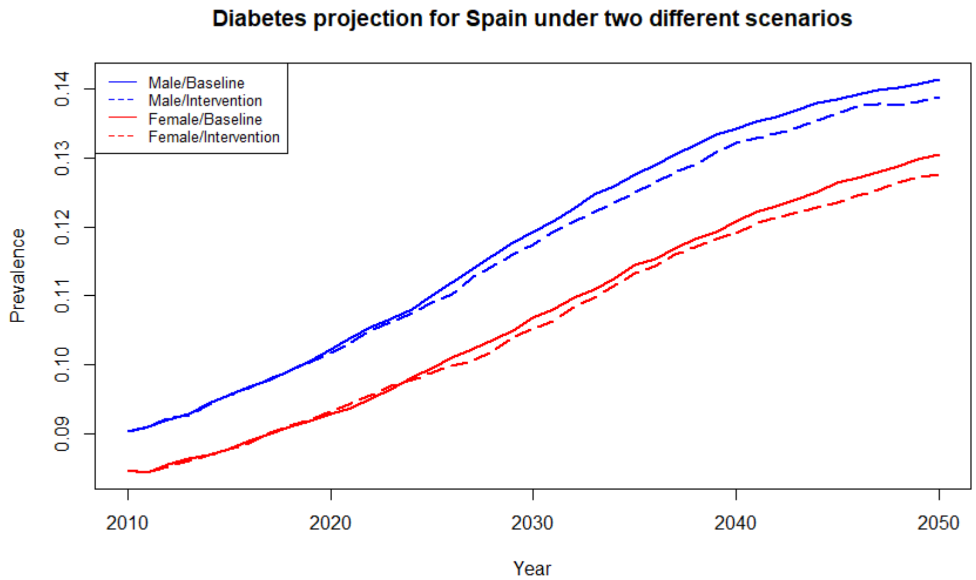
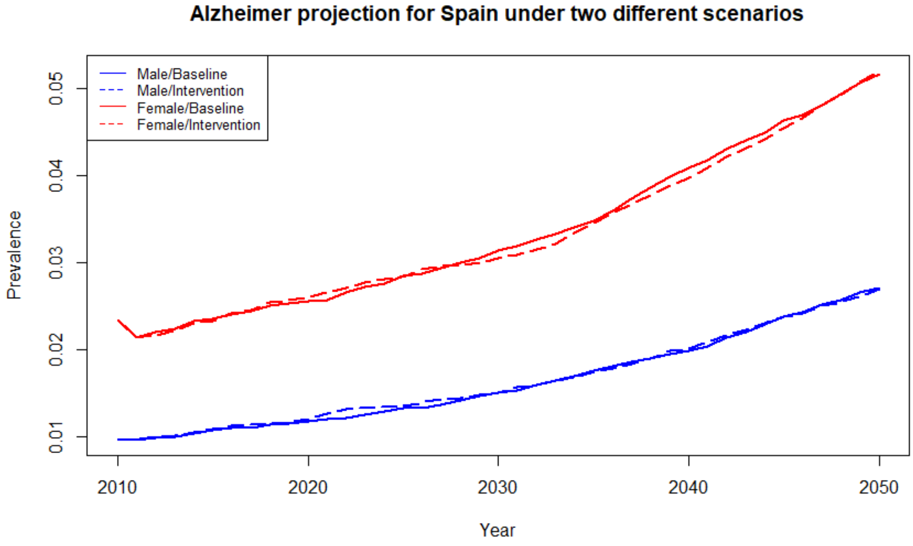
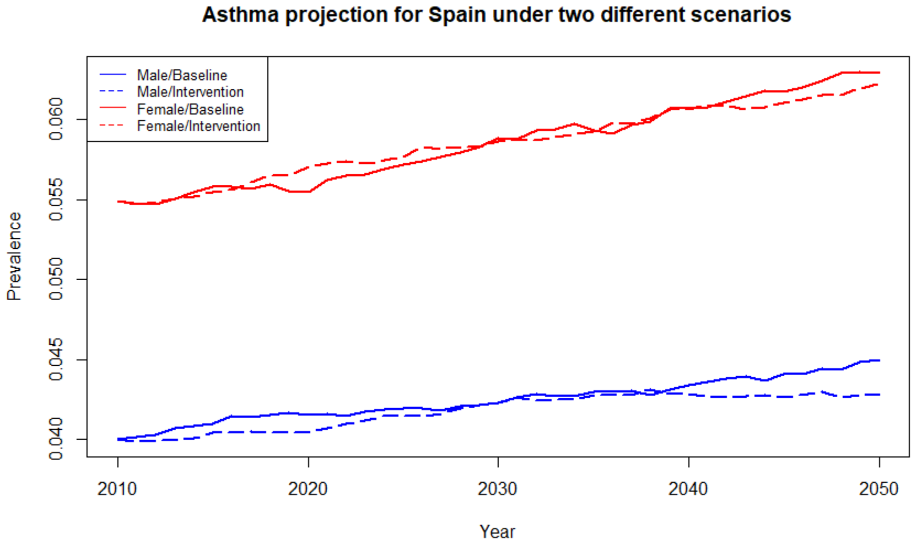
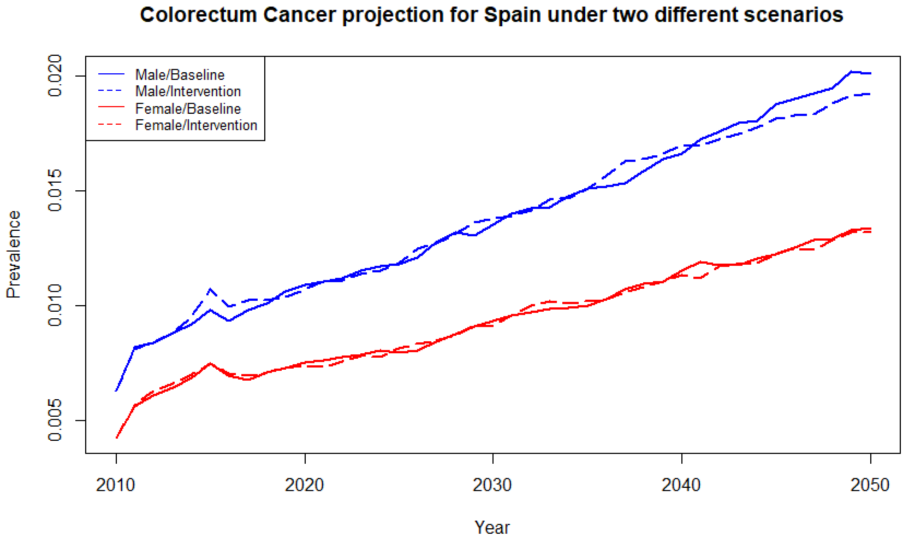
Spain

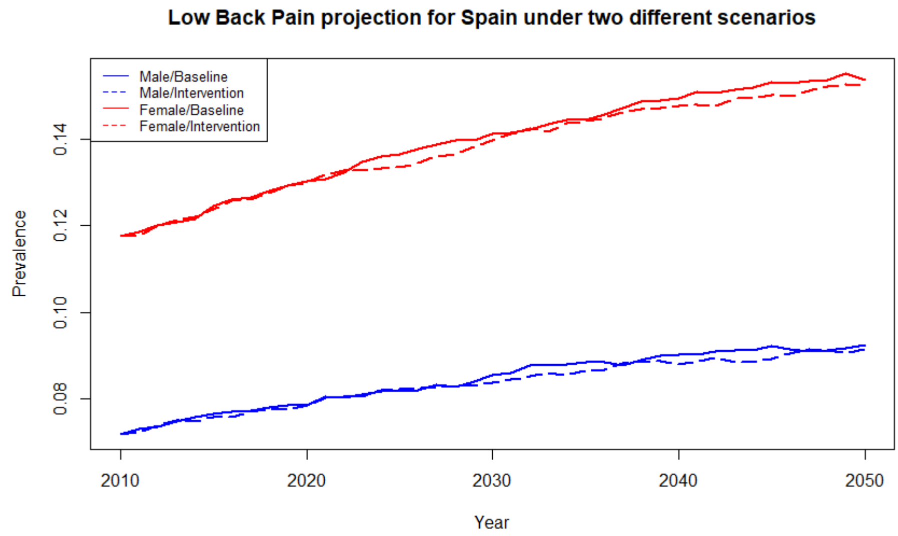


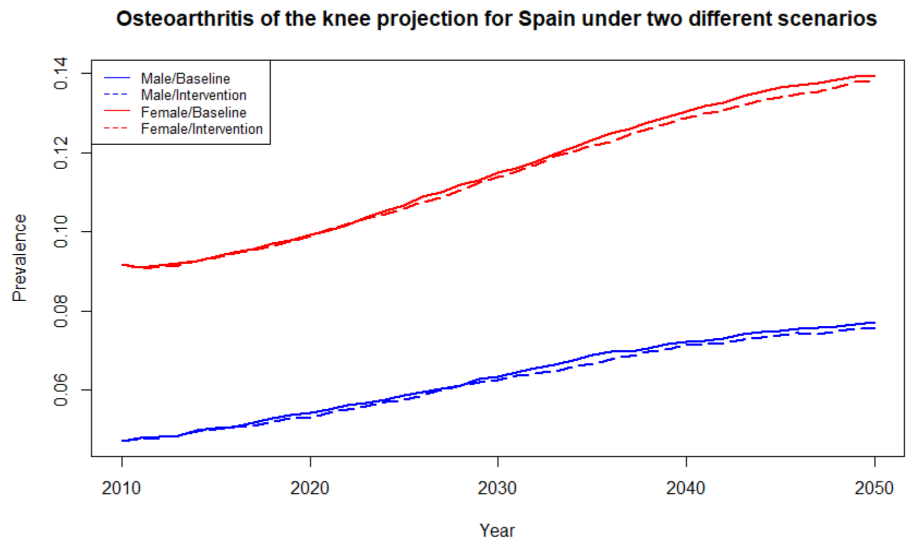


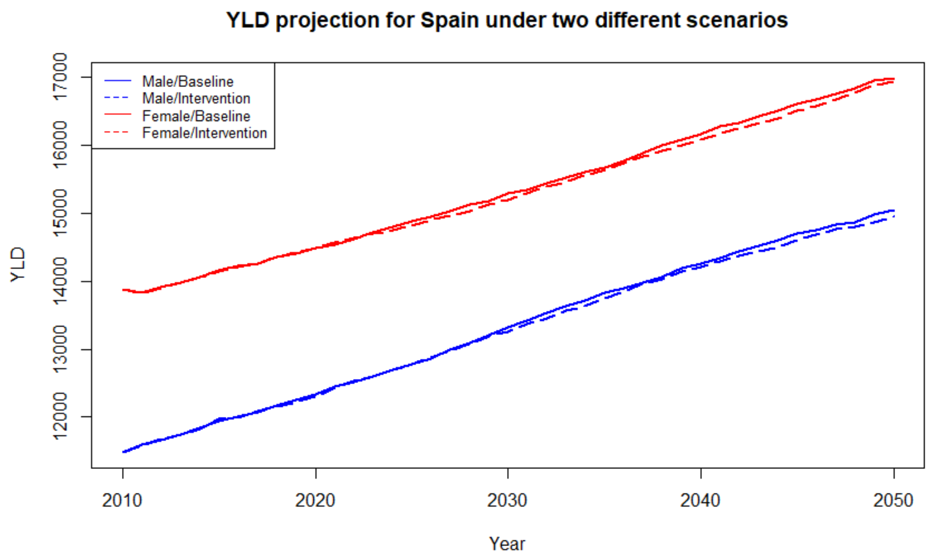

Alzheimer projection for Spain under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
Prevalence
0.01
0.02
0.03
0.04
0.05
2010
2020
2030
2040
2050
Year

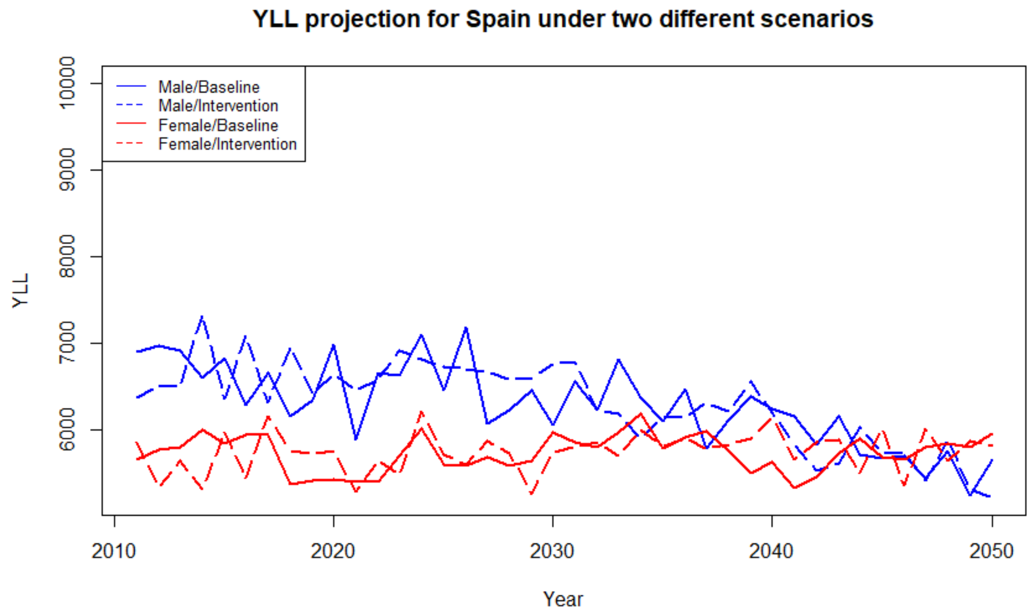

Asthma projection for Spain under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
Prevalence
0.040
0.045
0.050
0.055
0.060
2010
2020
2030
2040
2050
Year

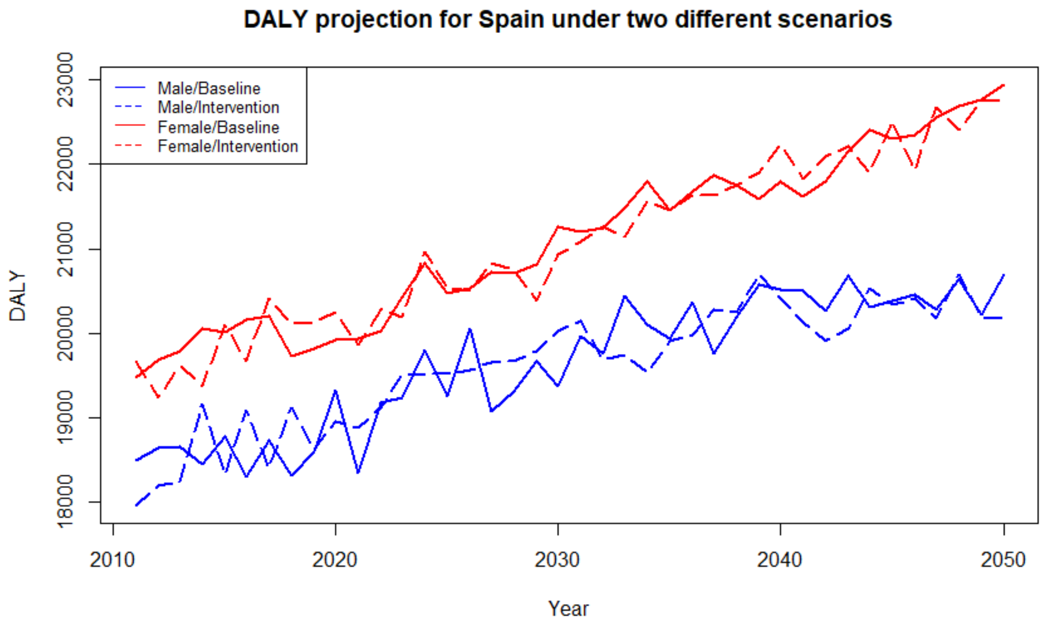

Colorectum Cancer projection for Spain under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
Prevalence
0.005
0.010
0.015
0.020
2010
2020
2030
2040
2050
Year


Low Back Pain projection for Spain under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
Prevalence
0.08
0.10
0.12
0.14
2010
2020
2030
2040
2050
Year


Osteoarthritis of the knee projection for Spain under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
Prevalence
0.06
0.08
0.10
0.12
0.14
2010
2020
2030
2040
2050
Year


YLD projection for Spain under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
YLD
12000
13000
14000
15000
16000
17000
2010
2020
2030
2040
2050
Year


YLL projection for Spain under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
YLL
6000
7000
8000
9000
10000
2010
2020
2030
2040
2050
Year


DALY projection for Spain under two different scenarios
Male/Baseline
Male/Intervention
Female/Baseline
Female/Intervention
DALY
18000
19000
20000
21000
22000
23000
2010
2020
2030
2040
2050
Year

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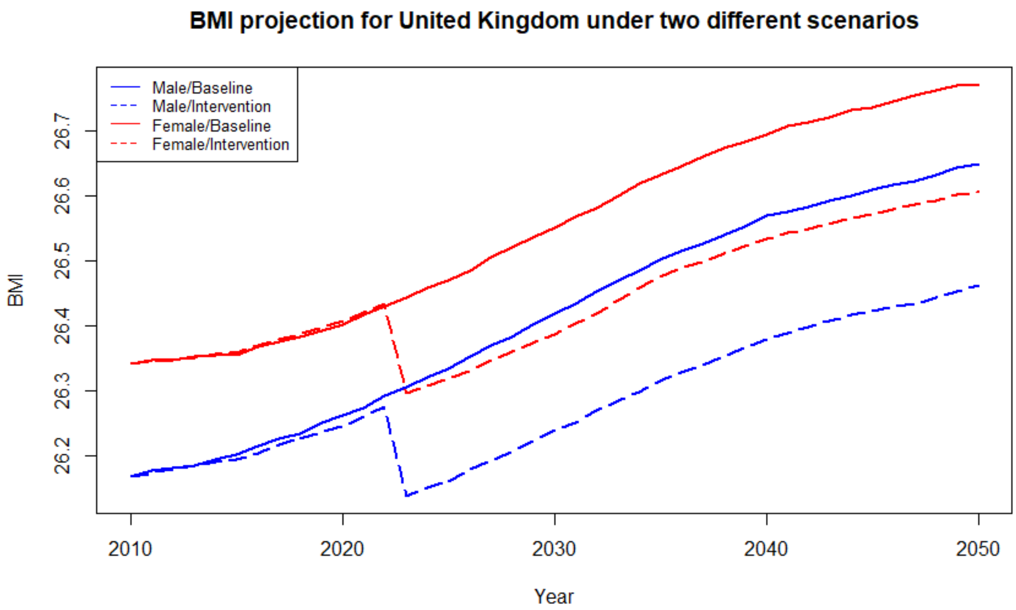
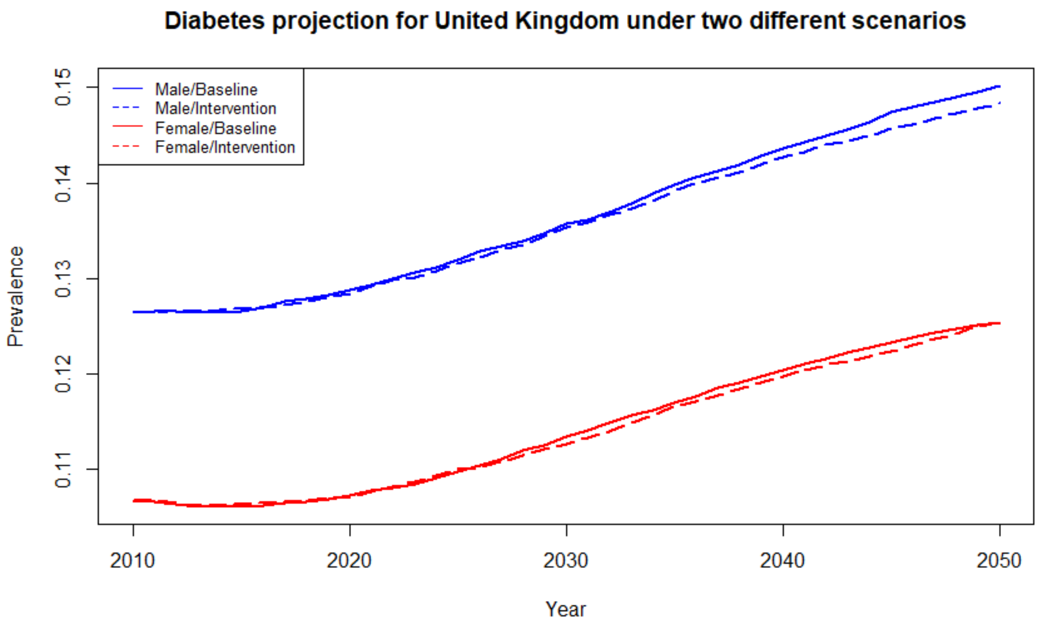
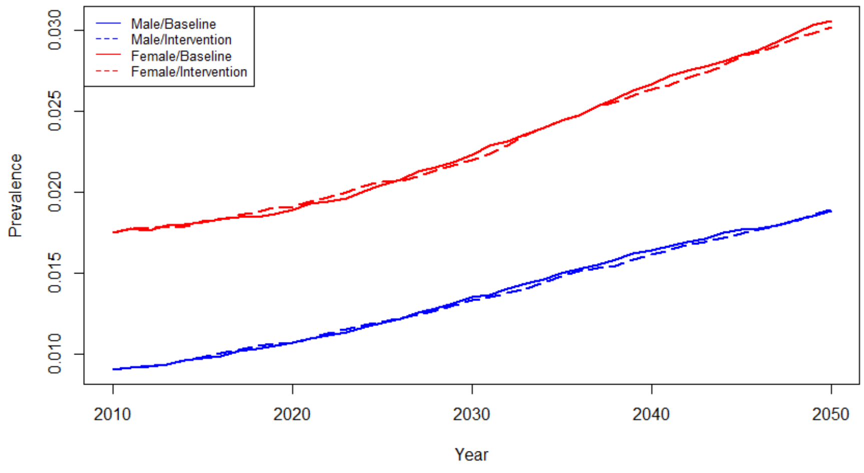
United Kingdom

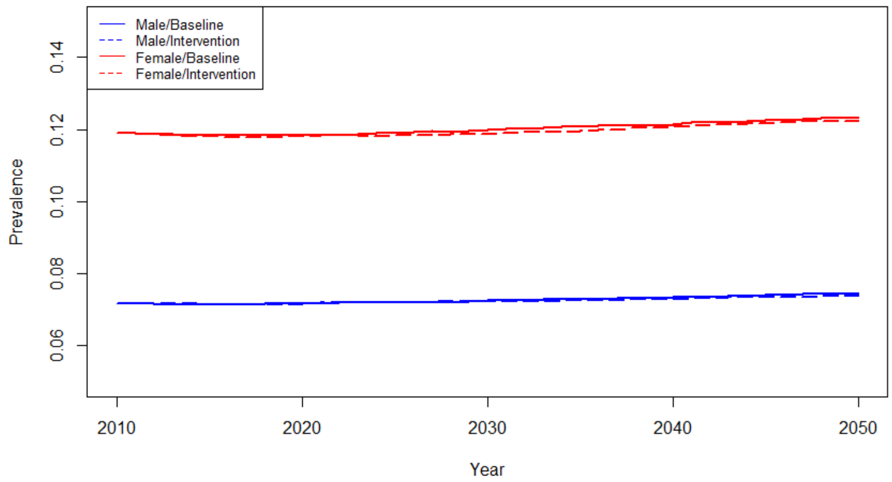




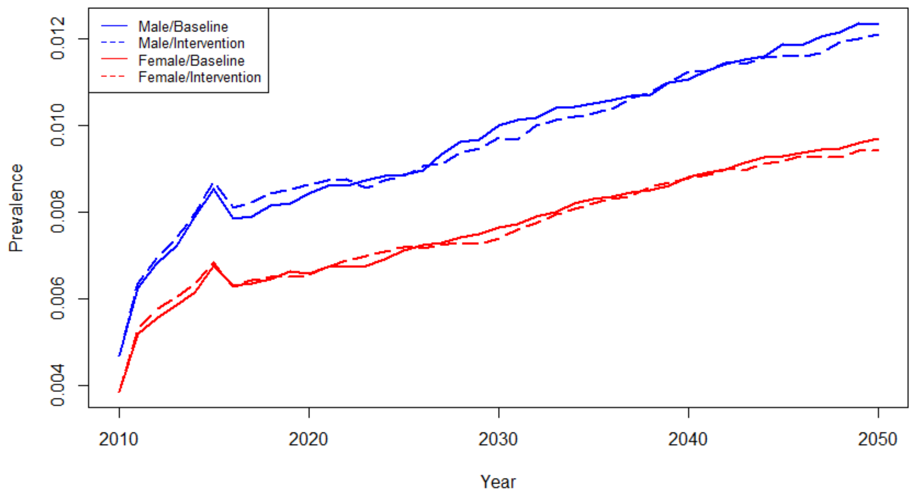
Alzheimer projection for United Kingdom under two different scenarios



Asthma projection for United Kingdom under two different scenarios



Colorectum Cancer projection for United Kingdom under two different scenarios



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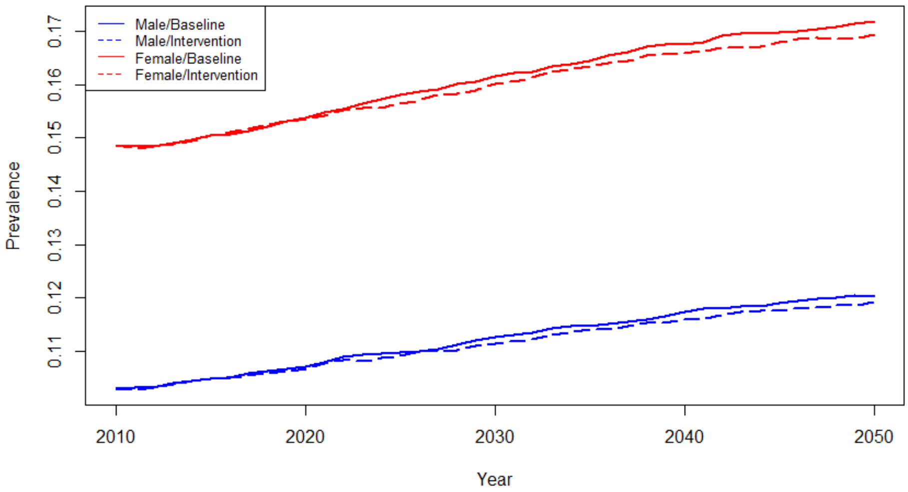
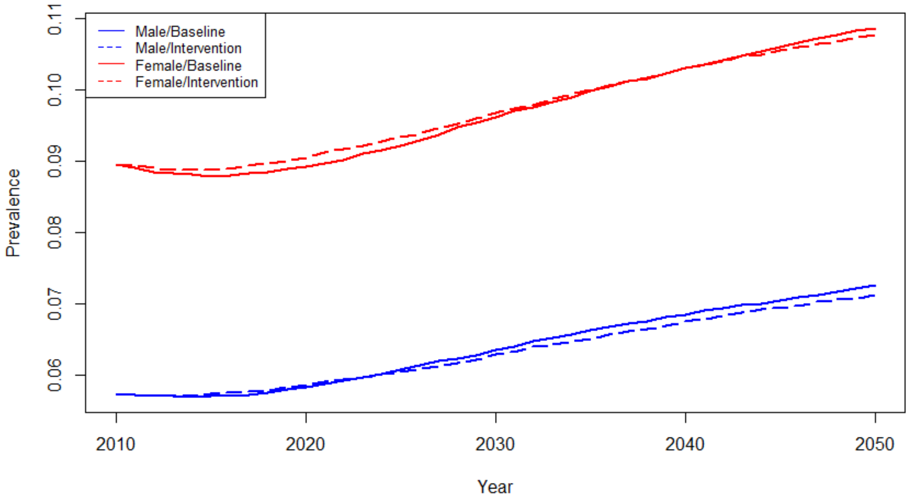
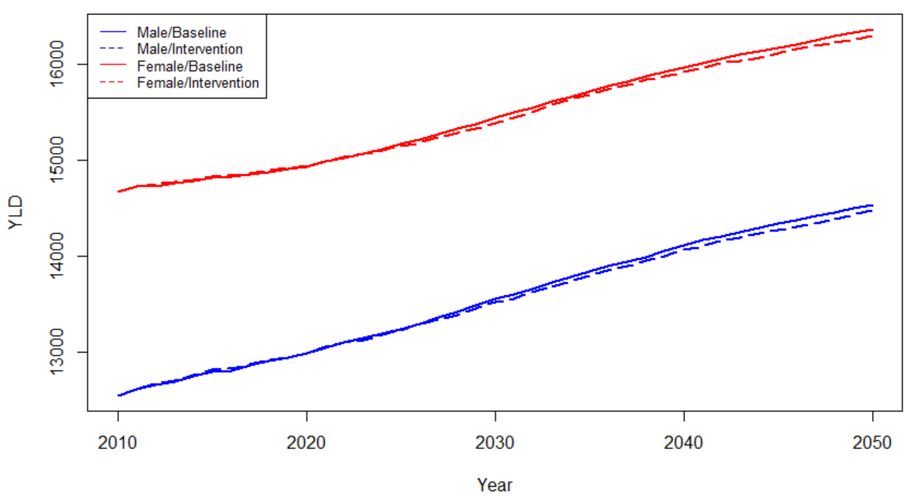
Low Back Pain projection for United Kingdom under two different scenarios



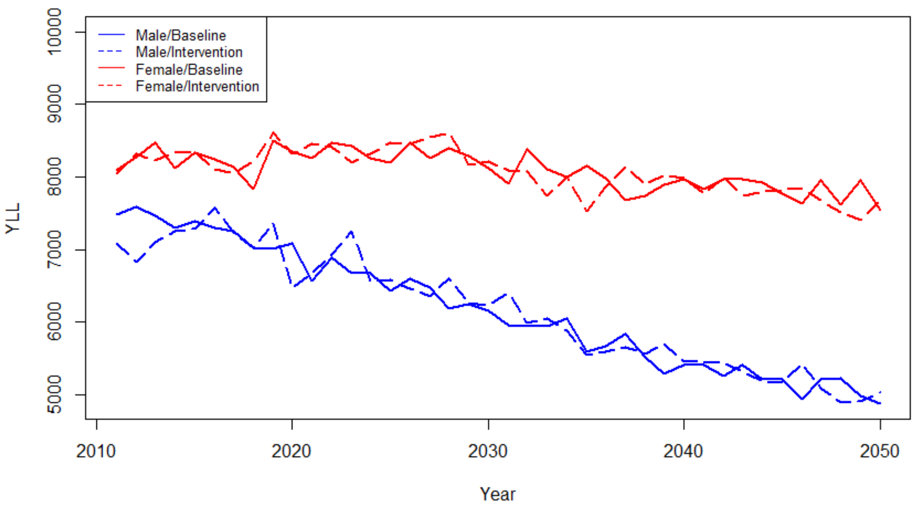
Osteoarthritis of the Knee projection for United Kingdom under two different scenarios



YLD projection for United Kingdom under two different scenarios



YLL projection for United Kingdom under two different scenarios



DALY projection for United Kingdom under two different scenarios