# Using *HealthSim* for ex-ante public policy analysis - the case of a Swiss policy reform

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**Abstract**

In this article, we adapt the model *HealthSim* to the specific context of the Swiss health care system to analyse a recently discussed policy measure aiming at reducing the increase in overall health care expenditures. The primary goal of the article is to present how *HealthSim* can be adapted to a specific context and what challenges arise. The second goal is to show the potential of *HealthSim* in analysing the multidimensional and heterogeneous effects of a policy measure in a complex health system. We find that it is possible, but difficult, to adapt the model to a specific context. The policy analysis shows that the proposed policy is likely to fail as it has extremely limited effects in almost all analysed dimensions.

## 1 Introduction

Providing a good and accessible health care system at an affordable price is a key challenge for many governments. Across the world, health care costs have risen over the last decade, and the share of GDP dedicated to health is very high, especially in high income economies. On average among OECD countries, health expenditures occupy 9% of GDP, with some countries such as the United States spending much more than this, up to 17% in 2016 (OECD, 2017). These large shares of health expenditures represent challenges for many countries that seek to spend less and ease the burden carried by the individuals and governments that bear the brunt of these costs. The large costs associated with many health systems are especially worrying because they are growing quickly. Average health spending per capita doubled from 2005 to 2015 among OECD countries, and these trends have not shown signs of slowing (OECD, 2017).

Reducing HCE or at least slowing its growth is a difficult task, because numerous actors intervene in a complex system, all with their own agendas and interests. The complexity of the health system makes any prediction of policy implications using linear models intractable and requires the use of models that are able to handle the complexity of the system. External factors such as population ageing, the link to other policy dimensions such as pensions and education and the possible trade-offs between equity, quality and costs further increase the complexity of the policy issue. All too often health policy is dominated by strong

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interest groups which are not necessarily looking at the whole complexity of the system (Campos and Reich, 2019; Giaimo, 2014).

In this article we illustrate how the *HealthSim* model (Chávez-Juárez et al., 2020) can be adapted to a specific context (Switzerland) and used to analyse the system-wide effects of a policy proposal. For this purpose, we analyse the proposal of increasing the minimum deductible in the Swiss Social Health-insurance System - which has been discussed in parliament in 2019. While we present some results analysing this policy in particular, the goal of this study is larger. First, we want to show what is required to adapt the general model presented in Chávez-Juárez et al. (2020) to a specific country and its legal framework. In this regard, we also discuss the possibility of inviting a larger group of stakeholders to better adapt the model to a specific context and use the model as a vehicle to discussion among stakeholders. Second, we want to show how the model works and in particular to what extent the model is able to produce system-wide results and be informative for policy makers.

We use the Swiss case for at least two reasons. First, Switzerland has the second–highest health expenditures per capita among OECD countries (OECD, 2019), and per capita expenditures have more than doubled since 2000 (World Bank, 2019). Both the level and growth of health expenditures are alarming not only to experts, but to the Swiss population as well; a recent public opinion poll showed that healthcare costs are the second most important issue to Swiss voters (Golder et al., 2018). Second, the proposed policy measure is a clearly defined small change to the rules rather than a general reform. This makes the analysis easier and allows us to focus the discussion on the possible use of the model. Of course, more complex reforms can also be simulated in such a model, but it is wise to start with a smaller one.

The remainder of this document is organised as follows: first, we briefly present the model, leaving much detail to the general presentation of the model given in Chávez-Juárez et al. (2020). Following the description of the general model, we describe the relevant adaptions made to customise the model to the Swiss case. We then present the results of our policy analysis and finally discuss the overall adaptation process with a special focus on challenges and opportunities.

## 2 The model in brief

In this section we briefly describe the main characteristics of *HealthSim*. A more detailed presentation of the model along with illustrative examples are presented in Chávez-Juárez et al. (2020). Technical details on the implementation of the model and the calibration can be found in the *Overview, Design concepts and Details* (ODD) protocol available as online appendix.

*HealthSim* is an agent-based discrete time model designed to be able to handle the complexity of health care systems. The base-model is very general and highly customisable to adapt to a large variety of health care systems. The current version of *HealthSim* is based on three key actors: patients, health care providers, insurance companies, which all interact within a context. The context includes a simplified panel of epidemiological incidences, the income and (initial) age distributions of the population and the regulatory context. Each of these characteristics can be contextualised to simulate a specific context, in this case Switzerland.

*HealthSim* uses time intervals of one week, meaning that every week a series of processes take place and all agents make decisions and take actions. Each type of actor, or agent, in the *HealthSim* has different

characteristics, adaptive processes, and actions.

**Patients** get sick with a certain disease or disease–group probability. This age-dependent probability is calibrated using real-world data. A patient can have several diseases at the same time, all affecting the overall health status of an individual. The patient has limited knowledge of the diseases as he or she only observes the overall loss of health status due to diseases. In each period, the patient analyses the subjective health status and its evolution with respect to the prior periods and decides whether or not to seek care. This decision is also affected by the expected out-of-pocket expenses, which depend on the health insurance plan. If they decide to visit a doctor, they comply with any diagnosis and treatments recommended by the doctor that they can afford. If not, they may choose to self-medicate.

Patients are heterogeneous with respect to their age, income and gender. Furthermore, their health statuses evolve endogenously and therefore heterogeneity in terms of health status emerges.

**Health care providers** decide how much to invest in the diagnosis of a patient in order to maximise their objective function, which depends on both their economic and medical success. Providers adapt their base investment in diagnostics over time in a learning process. We distinguish general practitioners (GP) and specialists, which also include inpatient care. If the GP is able to diagnose the patient, and their illness does not require a specialist, they prescribe them a treatment. Otherwise, they make a referral to a specialist. The model allows for provider heterogeneity in their quality, their maximal capacity of patients per week and a parameter capturing the relative importance of economic vs. medical success.

**Insurance companies** are subject to regulatory restrictions, and therefore their objective may vary depending on the context at hand. When they are permitted to make a profit, companies do so by setting premiums on health insurance plans with a fixed structure. When companies are not permitted to make a profit, they set premiums so that average costs equal average revenues. This process is adaptive, as insurance companies engage in learning in order to arrive at optimum premiums.

Several features make *HealthSim* suitable for the analysis of public policies. First, the simulation allows us to simulate the exact same population under different policy schemes and hence run experiments. This allows us to isolate the effect of a policy change. Second, the possibility of including heterogeneous agents allows us to analyse the effects of policy proposals on different parts of the population. The bottom-up modelling approach is on the one hand very intuitive given that we model the behaviour of each individual agent and on the other hand allows us to model the complexity of the system through the interaction of the different agents.

# 3 Adapting the model to the Swiss case

Let us now discuss how we adapt the general model presented in the previous section to the specific context of Switzerland, allowing us to analyse a real-world scenario. We start by highlighting some key aspects of the Swiss Health Care System and the proposed policy change. In a second step, we then explain how the model is adapted and calibrated to make it informative for this particular policy issue.

## 3.1 The Swiss Health Care System in brief

In Switzerland, the *Social Health Insurance* (SHI) is mandatory for all residents and can be purchased from private health insurance companies. SHI is strongly harmonised by the regulator and little choice is left to insurees. One variable of choice is the level of deductible, where buyers can choose among a few different values: 300, 500, 1000, 1500, 2000, and 2500 CHF[1]. Co-payment rates, stop-loss limits and the coverage are equal among all deductible levels and insurance companies. In addition to the deductible level, insurees can also choose between the traditional insurance and some recently added models including gatekeeping (by GP or by phone call) or some forms of PPO and IPA models. An important point about SHI is that insurance companies are not allowed to make profits.

In addition to SHI, individuals can freely choose to buy complementary coverage, on which insurance companies are allowed to make profits. Insurees can purchase both the mandatory and the complementary coverage from the same company or from different providers. Complementary insurance can include higher classes during a hospital stay (e.g. rooms with fewer patients), additional coverage (i.e. dental care) and a more flexible choice of hospitals (i.e. SHI include hospital care in the canton of residence in general, while complementary insurance can allow insurees to get treated in any hospital in Switzerland).

### 3.1.1 The policy proposal

Given the high and increasing costs of the health care system, policy proposals on how to reduce them are constantly discussed in the Swiss political system. In this study we focus on a proposal that only affects the SHI, but not the complementary insurance market. The policy proposal is to increase the lowest deductible level of currently 300 CHF to 500 CHF (effectively dropping the 300 CHF deductible).

Defenders of this policy proposal argue essentially that the lowest deductible of 300 CHF is too low to reduce problems of moral hazard, given that health care expenditures very quickly reach this limit. Moreover, an argument put forward by defenders is that this lowest deductible has not been modified for years despite increasing overall health care expenditures.

In contrast, opponents see a risk of overly affecting poorer and sicker people and thus making the system less equitable. Indeed, the share of out-of-pocket expenditures is in Switzerland already now very high as compared to similar countries (OECD, 2019).

Even when considering seemingly minor changes to the system, the consequences on average health care expenditure, distributional aspects of access to care and on the health status of the population are very difficult to predict. This is due to the complexity of the health care system. A higher deductible might have reducing effects on HCE when patients avoid medical care for minor issues. However, it can also be argued that postponing the seek for medical care can worsen medical conditions and eventually generate higher health care expenditures. The consequences on distributional aspects are even harder to predict: if the policy change yields a substantial reduction in the health insurance premiums, then it can be beneficial to the poorest households. However, facing a higher deductible might make them also more vulnerable in case of illness.

[1] 1 Swiss Franc (CHF) is roughly equal to 1 USD (July 2019)

## 3.2 Adapting the model structure

Given the nature of the policy proposal, the task of adapting the model to the Swiss case becomes somewhat simpler, because we can limit the simulation to the social health insurance market, which is by far the largest part of the whole system. We also exclude accidents from the model because in the Swiss system accidents form a parallel system which is not affected by the policy changes we test here. Within the SHI, we do not include different insurance models (e.g. PPO, IMA, etc), but only the traditional insurance model[2]. As a consequence, the products are even more similar, and we model the health insurance companies through a single representative firm. For this exercise, this simplification makes sense as it allows us to ignore a number of decisions made by patients concerning the type of plan demanded. These decisions are without a doubt important, but not necessarily for the policy proposal we analyse.

Furthermore, the SHI market permits additional simplifications to be made to the model through parameters. In the SHI system, insurance companies are not permitted to make a profit. Therefore, we limit insurance companies to set premiums based on average costs. Insurance companies do not engage in price discrimination based on health status, instead offering standardised plans with prices that vary with age. Therefore, we do not permit insurance companies to observe a patient's health status and maintain basic plan structure (deductible, co-pay) static. We also limit the model to the adult population because the policy proposal does not concern health insurance premiums for children and adolescents. All these simplifications are rather unrelated to the policy proposal and should therefore not affect the result. Of course, if we wish to analyse another policy measure for the Swiss context, these simplifications could be more problematic and would have to be revised.

## 3.3 Calibration and use of data

In addition to setting the parameters in a way to reproduce the legal and regulatory framework, we also need to calibrate the model to the Swiss context. First, we focus on the epidemiological profile and the available treatments, then on the health insurance pricing and finally on the income data.

### 3.3.1 Epidemiological profile

The most challenging part of the calibration is the epidemiological profile of the country. We proceeded in a sequential process by first selecting disease groups and then for each group we selected representative diseases. Finally, we included for each disease one or several treatments and estimated age-dependent incidence curves.

#### Selecting diseases to include

Given the flexibility of *HealthSim* to include any number of diseases, its adaption to a particular case require the selection of relevant illness according to the research question or to the simulated policy intervention. In our case, given that one of the most important outcomes is high and growing health spending in Switzerland, the selection of diseases was guided by the relative importance of their costs in the system. Wieser et al. (2018) provides information on the health care cost of 21 different disease groups in Switzerland. Six groups

[2]According to OFSP (2019a) almost 70% have either the traditional insurance model or a very slight variation with a GP gatekeeping. This slight variation resembles very much our implementation of the care seeking process

- representing 22% of the health care cost - were excluded because they are not relevant for the research question, either because they are not covered by the SHI (e.g. dental care, injuries) or because they are not directly related to a disease (e.g. prevention, well care). From the remaining 15 groups we included the 6 most cost-intensive groups and added two more groups (chronic respiratory diseases and diabetes) to have at least a few chronic diseases in our epidemiological profile. The finally selected 8 disease groups account for 78% of the relevant cost for our analysis or 61% of the total cost of the Swiss health care system.

Once we selected these groups, we consulted an expert (an active physician in the Swiss system) to identify up to four representative diseases for each category. The selection criterion for diseases were the availability of information, the cost generated by these illnesses, the importance in terms of incidence and finally obtaining a certain heterogeneity within each group. It is important to note here that this exercise is imprecise in at least two ways. First, by selecting a small number of 'representative' diseases we of course mechanically underestimate the costs by ignoring other diseases in the same group. Hence, we should not expect the model to reproduce the 61% of the actual health care costs in Switzerland that correspond to the selected disease groups. Second, for some categories we regrouped many sub-diseases into a single disease. The most striking example of this is cancer, where we include all types of cancer as one. From a medical perspective this is of course very imprecise, but when considering the data availability, it might make sense to focus on a larger group.

Table 1 displays the selected disease groups along with the selected diseases and treatments.

**Treatments**

Similar to the selection of diseases within groups, we also made a small selection of the most common treatment types for each disease. In some cases, only one treatment is available, while for other diseases multiple treatments were identified. In some cases, these different treatments are sequential. COPD is a good example, where a simple inhaler is appropriate for low severity, while the treatment has to change when the severity increases over time. In other cases, the treatments are mutually exclusive - for instance for an acute bronchitis cold 'self-medication' might simply be a simpler for of medication as compared to the mix of drugs prescribed by a GP. For each treatment we made a cost estimate based on either publicly available prices of drugs or directly from the regulated price lists for medical services[3].

**Incidence**

For the age-dependent incidence calibration we use specialised incidence estimations from existing literature, when available. For chronic diseases we estimated incidence from prevalence, when no incidence data were available. In most cases we used data from the *Federal Statistical Office* (FSO, 2019), but for some diseases (for example, hypothyroidism and hyperthyreose), we had to consult information from similar countries (Germany) because no data were available for Switzerland.

### 3.3.2 Insurance prices and plans

With respect to health insurance, the calibration was substantially simpler. We use the average cost of the standard social health insurance plan by age and deductible level as published in OFSP (2019b, Table T

[3]We use the TARMED system for treatments that are generally provided in outpatient care and SwissDRG for inpatient treatments.

Table 1: Selection of disease groups, diseases and treatments

| Disease group | % of HCE | Selected diseases | Selected treatments |
|---|---|---|---|
| Cardiovascular | 15.6% | Heart attack | 1) Emergency response<br>2) Reduce risk of heart attack (plavix)<br>3) Surgery |
| | | Hypertension | 1) Captopril |
| | | Stroke | 1) Emergency response<br>2) Rehabilitation |
| Chronic respiratory | 2.5% | Asthma | 1) Short-term inhaler<br>2) Long-term inhaler |
| | | COPD | 1) Inhaler and other drugs to reduce inflamation<br>2) CPAP<br>3) Rehabilitation, Therapy (O2 at home) |
| Communicable | 4.7% | Acute Bronchitis | 1) Self-medication (e.g Ambroxol)<br>2) Ambroxol + Paracetamol + Syrup |
| | | Pneumonia | 1) Antibiotics and other drugs<br>2) Intensive care |
| | | Common cold | 1) Self-medication<br>2) Analgesics |
| | | Influenza | 1) Self-medication<br>2) Simple drugs<br>3)Antiviral medication |
| Diabetes | 1.5% | Diabetes | 1) Insulin and/or metformin |
| Urogenital, blood and endocrine | 6.8% | Hypercholesterolemia | 1) Selipran |
| | | Hyperthyreose | 1) Anti-thyroid medications and beta blockers<br>3) Surgery |
| | | Hypothyroidism | 1) Hormones |
| Mental | 10.6% | Depression | 1) Antidepressant<br>2) Therapy each month plus antidepressant |
| Musculoskeletal | 13.4% | Osteoarthritis | 1) Simple pain killers<br>2) Stronger pain relief, anti-rheumatic drugs, etc.<br>3) Surgery |
| Neoplasms | 6.0% | Cancer | 1) Chemotherapy<br>2) Surgery<br>3) Radiotherapy + Chemotherapy |

3.03). In order to consider the fact that our epidemiological profile in the model is only part of the full profile, we multiply all premiums by a constant factor (0.3676[4]) in order to keep the relative prices intact. This adjustment is not of major importance, but it allows us to have a model that requires less periods of adjustment.

### 3.3.3 Population and income data

In order to simulate the Swiss population and its salient characteristics, we simulate the initial distributions of age and income using random variable distributions. The initial age distribution is captured by a two–part distribution; the distribution mimics a uniform distribution from 18–58 years old, then tapers off linearly (in expectation) from 58–100 years old. This distribution is then taken over by endogenous illness and mortality in the model.

In contrast, the income distribution remains exogenous throughout the model and is simulated with a log

[4]This number was estimated by selecting those costs reported by Wieser et al. (2018) that the model is supposed to reproduce.

normal distribution. We opt for this parametric approach, because we do not have micro-data on disposable income. Therefore, we used summary statistics on the mean, standard deviation and median of incomes and data on the average number of people per household to fit a parametric distribution. The resulting distribution is a log-normal distribution with $\mu = 6.7671$ and $\sigma^2 = 0.1828$ which translates into an average per capital disposable income of roughly 950 CHF[5].

### 3.4 Summary of the adaptation process

A key goal of this study is to discuss to what extent it is possible to adapt the more general model presented in Chávez-Juárez et al. (2020) to a specific public policy analysis taking place in a specific context. Hence, before moving to the results, let us recapitulate a few lessons learned from the adaptation exercise.

The fact of using a relatively simple policy analysis that allowed us to focus exclusively on the social health insurance in Switzerland helped us considerably in the adaptation. Almost no coding was necessary as most adaptations were possible through parameter changes. However, if the goal was to include also the complimentary health insurance plans which are not mandatory, then the adaptation would require some additional coding.

In terms of calibration the exercise showed us that the most difficult part is the epidemiological profile and the treatments. Not only because of the amount of data that requires calibration, but also because of a lack of information and foremost because of the complexity of the topic. In the discussion section we discuss collaborative techniques and methods that could help in this process.

Finally, the calibration of income and insurance data was relatively easy and could be done in a more precise way without too much complication.

## 4 Results

We will now present the result of our simulation exercise in two steps. First, we present baseline results where no policy change was simulated. We then present the policy intervention results.

To obtain the data underlying all the presented results we generated a[6] with 10'000 individuals and simulated the model for 1560 ticks (30 years). For the same population, we ran three different policy settings: baseline, minimum deductible at 500 and minimum deductible at 1500. The policy intervention was introduced in tick 785, making the policy effective as of the $16^th$ year of our simulation. To simplify the reading of our results we centre the time scale around the policy intervention.

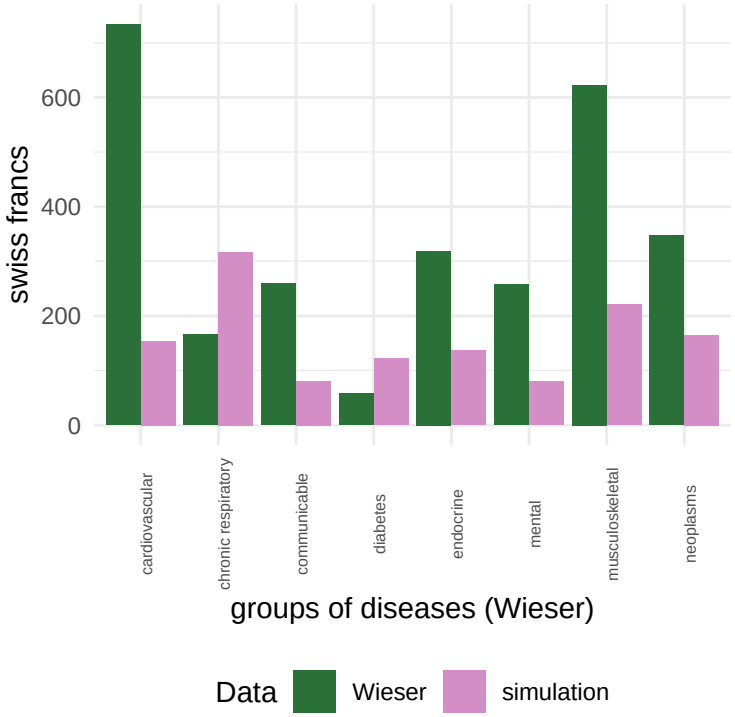
[5]Note that this does not correspond to the official disposable income statistics, because we use a different approach. The official disposable income is after paying the mandatory health insurance, but before paying for nutrition and housing for instance. In contrast, for our model we add the average cost of social health insurance but deduce all general expenditures such as housing and nutrition.

[6]We also ran the model under different random seed (i.e. different initial populations) and found that the results are very stable. We therefore decided to focus on a larger population with a single run to present the results. This choice was driven by the fact that some disease incidences are quite small and using smaller populations could be problematic for those diseases.

## 4.1 Baseline results

In order to analyse the ability of the model to reproduce the total health costs of illnesses, in Figure 1 we compare our results to estimations of health care expenditures by disease categories provided by Wieser et al. (2018).

Figure 1: Cost distribution of group of illnesses




Given that our model does only include a subset of diseases for each group, we expect our cost estimates to be below those reported by Wieser et al. (2018). The goal of the comparison is simply to show to what extent the model is similar to the actual situation, which should then allow the reader to better understand the results in the remaining figures.

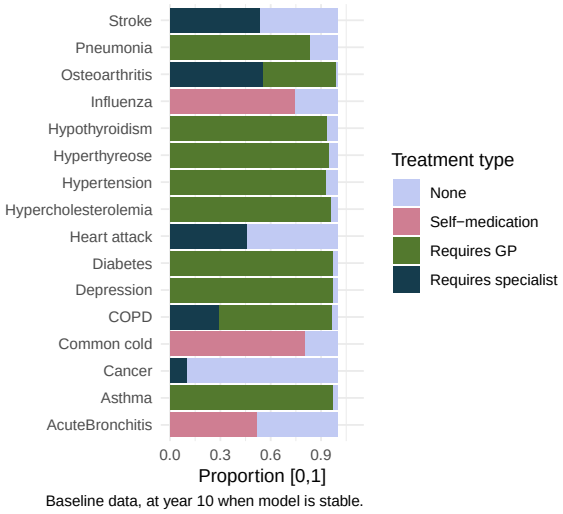
Overall, health expenditures by disease represents roughly half of Wieser et al. (2018) estimations on average. This is due to the fact that for each disease group we only include up to four diseases, while in reality more are present. In all but two groups the produced costs in the model are lower than the values observed in reality. The two exceptions are *chronic respiratory* diseases and *diabetes*. In both cases it is likely that our treatment mix is somewhat too expensive as compared to the available treatments. For instance, in the case of diabetes we only include insulin intake and leave aside possible behavioural management and prevention actions. For the remaining groups we generally underestimate the cost, but in roughly similar proportions.

Overall, we can see that our calibration exercise is generally producing lower costs as we would expect from a partial calibration.

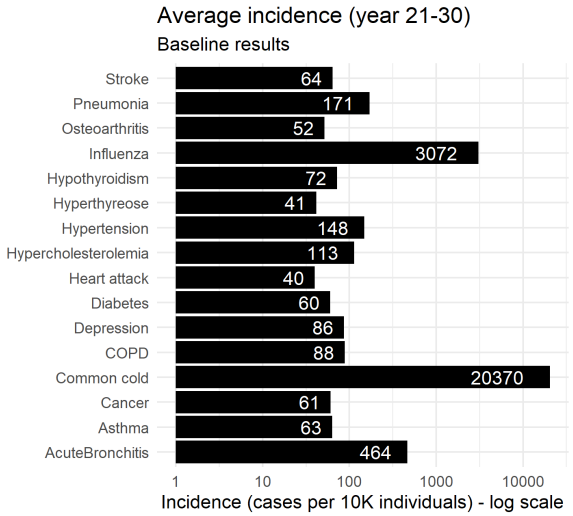
A second endogenous element of the model worth discussing is the distribution of treatments by type

and diseases. Figure 2a displays the distribution of types of treatment used for the different diseases. We distinguish four types of treatments: self-medication, treatments that require the intervention of a general practitioner, treatments requiring the intervention of a specialist, and no treatment. Note that self–treatment does not necessarily imply that a doctor was not consulted, as the model permits GPs to recommend self–treatments as well as non–specialist prescriptions.

(a) Treatment distribution by illness




(b) Incidence




From the graphic we can see that the most urgent illnesses we include in the model (stroke and heart attack) have by far the highest percentage of specialist treatment, which we would expect given the severity of the condition and the intensity of intervention on average. The remaining proportions have no treatment, suggesting that those events had fatal consequences for the patients.

More interestingly from the model perspective are the treatment distributions of less severe illnesses such as *Influenza*, *Common cold* and *Acute Bronchitis*, where we can observe different types of treatments. In these cases, individuals frequently elect to not treat the illness and simply wait until the illness clears up on its own; only in slightly more than half of the cases self-medication is used.

The most interesting cases are COPD and Osteoarthritis, where a mix of GP and specialist treatments are used. The endogenous election to seek specialist attention may depend on several factors, but of central importance in the model is the severity of the condition, as higher severity prompts patients to seek more effective specialist treatments. This heterogeneity in treatments is the result of the complex system involving heterogeneous agents.

Finally, the large proportion of non-treated cancer is due to the fact that symptoms emerge only very gradually and therefore many individuals live without treatment due to a lack of diagnosis.

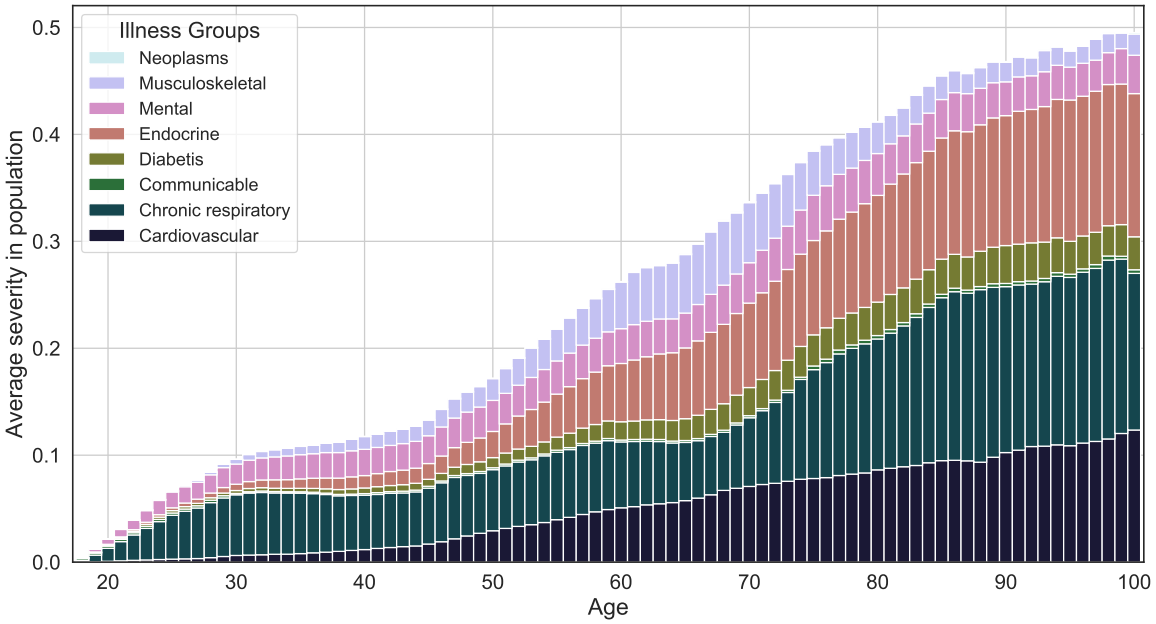
Disease incidence rates as generated in the model are displayed in Figure 2b. Incidence rates per 10,000 people are based on events, and therefore the number can be above 10,000 (such as in the case of Common Cold), as patients may suffer a common cold more than once a year.

These results are not the result of endogenous processes in our model, as disease incidence remains an exogenous probability throughout the simulation. Therefore, these results are not informative of the

performance of the model, but rather serve to inform the discussion of other results by showing the importance of a particular illness in the model.

Probably more interesting than the simple incidence values is the distribution of severity by disease group along the age distribution. Figure 3 displays the average severity by age of all 8 disease groups.

Figure 3: Average severity of illnesses by age and illness group

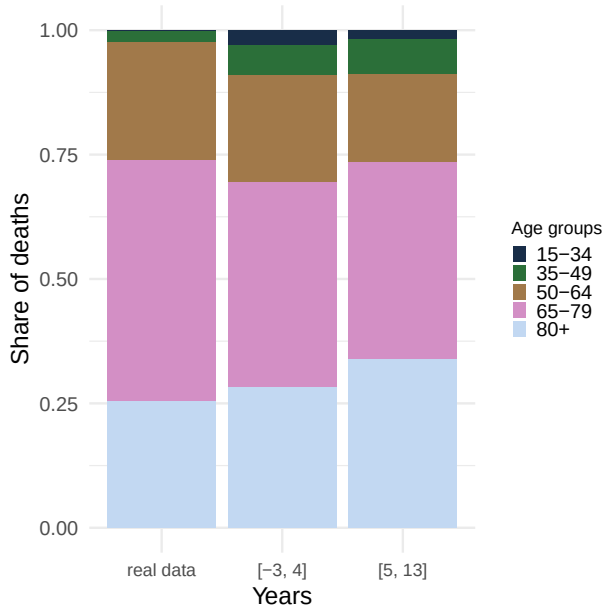



We can see that according to the model overall morbidity (total height of bars) increases non-linearly with age. The sharpest[7]. increase in morbidity is observed starting around the age of 45 up to the age of 85. This increase is mostly driven by stronger increases of endocrine and cardiovascular diseases at these ages. Note that two disease groups are almost non-existent in this graph: neoplasms and communicable diseases. The reason for neoplasms not showing up here is most likely the rather small number of patients as compared to the total number of agents. For the communicable diseases a we have mainly very short-run diseases which do not last for more than 2-3 ticks and therefore become very small when averaging over a longer period.

Let us now turn to the analysis of the end of life, where Figure 4 compares the share of deaths by age in the model to real mortality data. Overall, the model mimics the proportion of deaths in reality to a reasonable extent, with the proportions nearing the true values to a greater extent as the simulation advances. The model overestimates the share of deaths absorbed by the youngest age category, patients aged up to 49 years, and underestimates the share absorbed by individuals between 50 and 80 years. The slight underestimation for the group between 50 to 80 years could be due to our assumption that disease severities sum up independently, while some interaction effects could be present in reality. Overall - however - we would argue that the results presented in Figure 4 suggest that the model works reasonably well, especially considering that death is the result of multiple endogenous processes in the model.

[7]We do not consider here the increase between 18 years and 30 because our agents start in the model at the age of 18 and we therefore cannot capture chronic diseases starting earlier in life

Figure 4: Age distribution at death




**Notes:** Years values in brackets refers to simulation years (52 ticks). In all figures, 0 refers to the year of simulation where policy starts. In this figure, we contrast real data to results of three simulation periods: one period around the ticks when policy starts [-3, 4] and another after policy [5, 13].

## 4.2 Policy intervention

We implement two policy experiments in which the minimum deductible offered by insurance companies is raised. In one experiment, we raise the minimum deductible from 300 CHF to 500 CHF, while in the other we increase the intensive margin of the policy change, raising the minimum deductible to 1500 CHF. In particular, raising the deductible to 500 CHF is an attractive experiment because it is a policy that has been debated in Switzerland as a way to combat high health care expenditures. By analysing the 1500 CHF case as well, we test whether intensifying the treatment generates larger effects.

The following results can be interpreted as experimental results in the sense that we simulate the exact same population under different policy schemes. To avoid simulating the policy measure during the somewhat unstable initialisation phase of the model, we run all simulations for 15 years, then implement the policy, and run it for another 15 years to analyse short-, medium- and long-run effects.

Raising the minimum deductible is equivalent to raising the marginal costs of the patient's health care expenditures that fall within the range of the change. Only individuals that had a deductible lower than the new minimum and who did not yet reach their annual deductible are directly affected by the measure.

Figure 5 shows total health care expenditures over time separated by the baseline (counterfactual) scenario and the two policy schemes.

The policy changes appear to have little to no overall effect on total spending, as the trends and levels under the two policy changes closely follow the baseline evolution. Figure 6 confirms this finding; total expenditures show little perceptible difference.

Under the minimum 500 policy, the distribution of costs between patients and insurance providers closely

Figure 5: Total HCE by policy scheme

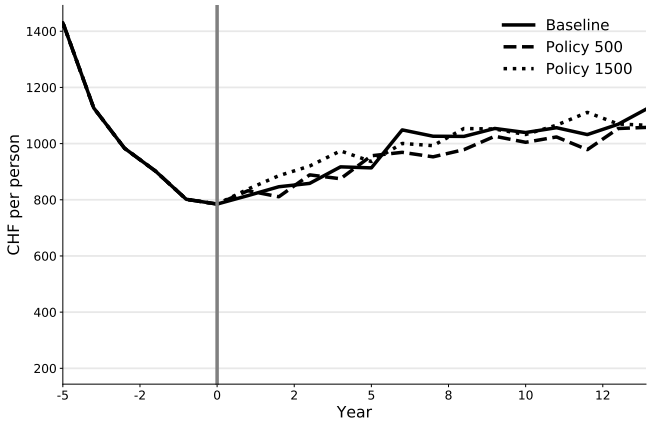
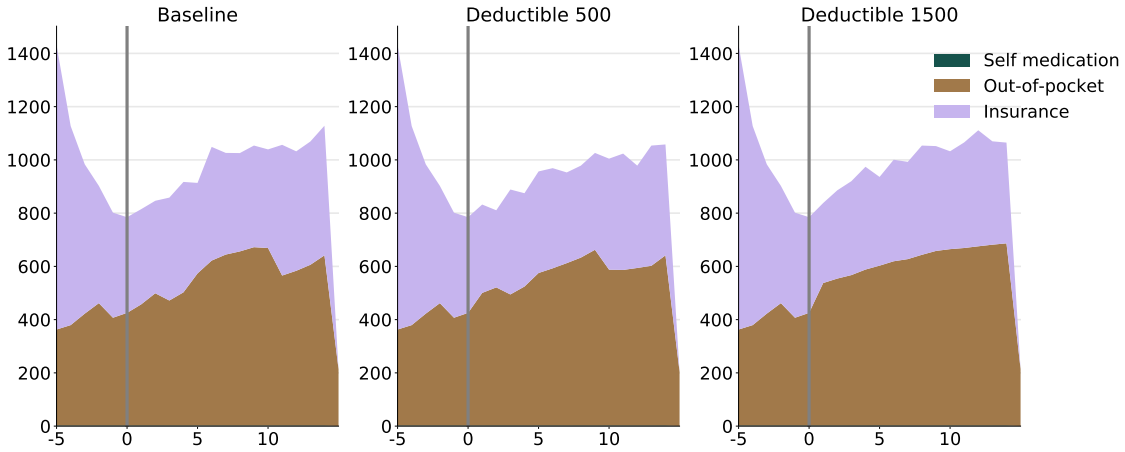



Figure 6: Composition of health expenditures

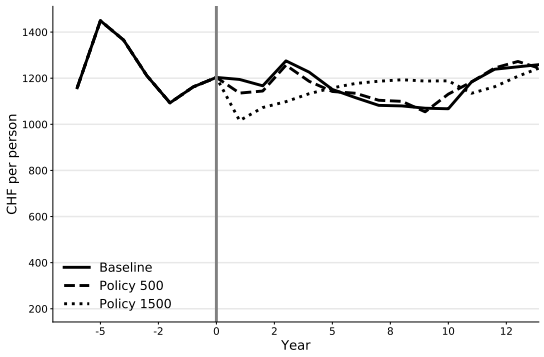



mirror the baseline case, while in the 1500 scenario patients absorb a greater share of total expenditures, although this total is largely unaffected. This provides evidence that the change is not significant enough to deter moral hazard in patients; they simply absorb the costs without significantly altering behaviour.

Figure 7 shows in clearer detail this result: under the 500 CHF deductible the total cost absorbed by patients, measured as the sum of premiums, co-payment and spending on self–medication, is almost identical to the baseline scenario.

The 1500 CHF deductible has a sharp negative effect on patient spending in the short run, but this result is driven by the slow adaptation of insurance plan premiums in the model. Given that insurance companies set premiums according to historic average costs, they do not forecast the entry of high–expenditure patients into higher deductible plans when the lower deductibles are eliminated. As a consequence, in the model, patients who previously preferred low deductibles with higher premiums move into high deductible plans which previously had lower premiums and enjoy lower overall costs as a result. However, over time, insurance

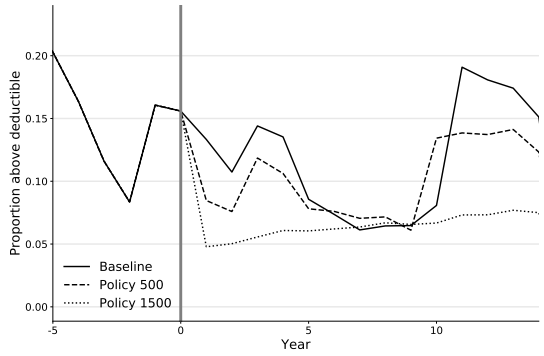
Figure 7: Costs absorbed by patients




companies adjust premiums to the new, higher costs, and this surplus enjoyed by patients is eliminated. Therefore, in the medium to long run, spending under this policy converges to the baseline level. This process that would likely be much faster in reality, as insurance companies anticipate these changes, and would adjust premiums accordingly, leading us to believe that this initial improvement in the patient–born costs would not be observed.

Finally, Figure 8 confirms the mostly mechanical drop in the percent of patients that reach their deductible in a year, from an average around 15% to around 10% in the case of the 500 CHF deductible and slightly more than 5% in the 1500 case. Not presented are results disaggregated by decile, as we find that the effects observed here on average are similar when analysed by decile; each decile experiences an almost parallel shift in spending.

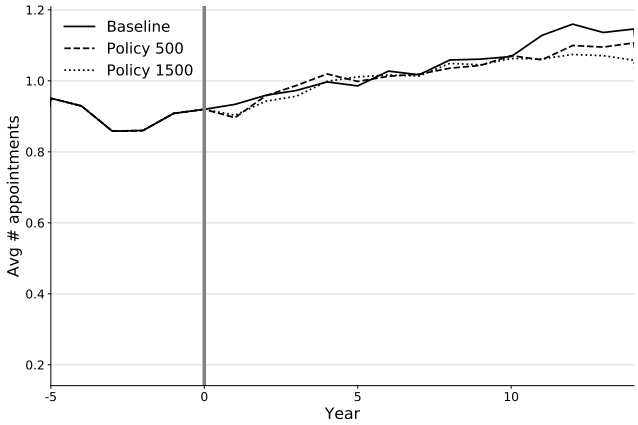
Figure 8: Percent meeting their deductible by policy scheme




We have seen the effects of the policy on total spending are very small and we mostly observe a shift of who pays how much, rather than an effect on total spending. Let us know have a look at the secondary effects on patient behaviour and health. Figure 9 shows the average number of appointments per patient per year. Similar to the results on spending, the policy changes make little difference in the long run in

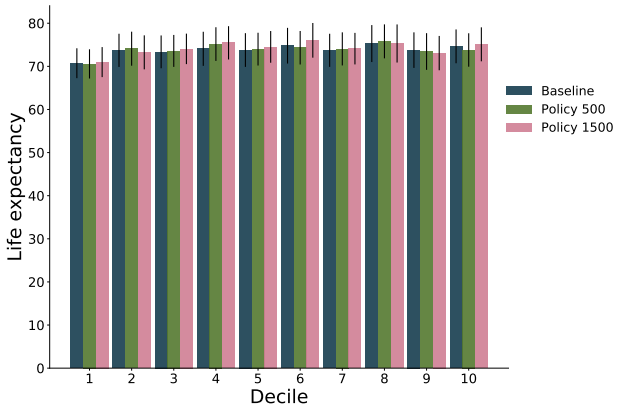
the number of appointments sought out by patients. In the very short run, we observe a slight decrease of appointments, which is recovered within 2 years. This provides evidence that in terms of seeking treatment, for most illnesses and most patients the policy change is simply too small to make a difference.

Figure 9: Appointments by policy scheme




Finally, let us have a look at the most comprehensive measure of health - life expectancy. Figure 10 displays the life expectancy by decile and policy setting. If the policy would have negative effects on patients' health, we should see a decrease in life expectancy under the two policy schemes.

Figure 10: Life expectancy by decile




This is not observed in Figure 10 where the bars for the different policy schemes are never statistically different from each other. The only difference that can be observed is a slightly lower life expectancy for the first decile.

In summary, the policy change shows a negligible effect on average health status, slight changes in appointments, and an important increase in the system costs absorbed by patients, though overall costs are unaffected. These results provide evidence that while the policy does not appear to impose negative effects

on population health, the change may not represent a significant enough change to reduce costs in the long run.

# 5 Discussion and conclusion

In this article we have presented the adaptation of the general model *HealthSim* presented in Chávez-Juárez et al. (2020) to a specific context (Switzerland) and a specific public policy proposal (raise of the minimum deductible level in the social health insurance). The two main goals of the study are first to show to what extent it is possible to adapt the model to a specific context and second to present how a public policy analysis can be carried out using *HealthSim*.

With regard to the adaptation process we already outlined the main challenges we faced in section 3.4, here we focus on ways this process could be improved. Probably the most important challenge of the process is to calibrate the epidemiological profile, where knowledge from medical experts is of paramount importance. Insights from medical staff would also be beneficial to refine some of the processes included in the model. At the same time, many other stakeholders in the health system have valuable knowledge about processes. We therefore suggest the use of collaborative and participatory modelling techniques. Collaborative and participatory modelling refers to a family of methods and frameworks for including stakeholders in the modelling process with varying degrees of participation and agency (Voinov et al., 2016; Basco-Carrera et al., 2017). Such collaborative modelling approaches have been successfully implemented in combination with agent-based models in a variety of topics[8]. Here we distinguish interdisciplinary collaboration, which can be understood as researchers from different disciplines collaborating in a single model or modelling exercise, from collaboration with stakeholders and decision makers, who possess experiential knowledge of the system. Both types of collaboration have the potential to increase the accuracy of model parameters and assumptions, and the model presents ample opportunities for future collaboration in the calibration process. Beyond improving the model by applying collaborative modelling approaches, the necessary stakeholder involvement can also be beneficial as such. We outlined in the introduction that the health system is characterised by many different and sometimes diverging agendas and interests. Understanding the system dynamics in a group of different stakeholders might help improve the discussion and communication among stakeholders.

In relation to the second goal of the study - showing how the model can be used for a public policy analysis - we were less successful. The problem is that the analysed public policy does not seem to have a major impact and therefore we were not fully able to illustrate the richness of the approach. The model is able to identify winners and losers of a policy, point to different effects in the short-, medium- and long-run and inform stakeholders in general about a wide variety of variables. Unfortunately, our public policy analysis produced very small effects which inhibit a clear illustration of these strengths. Of course, this needn't be negative as indeed a policy proposal might have less than expected effects and hence the model would be useful in an ex-ante analysis to show that implementing the policy might not be worth the effort. In Chávez-Juárez et al. (2020) we present a series of more illustrative examples in a strongly simplified context to give a clearer idea of the possibilities.

[8]See for instance: Learmonth et al. (2011) for an example on environmental sustainability or Wellman et al. (forthcoming) for an example on organisational structures.

Overall, we would argue that a calibration and adaption of the general model presented in Chávez-Juárez et al. (2020) is possible, but not straightforward. Much medical information and data is required to calibrate the model and fully reproduce the cost structure of a health system. Of course, in many cases a full representation of the system is not completely necessary and policy analyses can be run based on a simplified context.

The policy analysis of the Swiss proposal to raise the minimum deductible showed little to no effect. All seem to point to the fact that the proposed increase of the minimum deductible only affects a very small number of individuals and can therefore not substantially affect the system wide dynamics. We were not able to confirm nor reject the arguments of promoters or opponents of the policy.

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