HealthSim: a flexible general purpose agent-based model of health care systems

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Abstract

In this article we present *HealthSim*, a flexible agent-based model of the health care system. *HealthSim* is a multipurpose model that has been designed as core model which can be adapted to various country specific contexts. It uses calibrated data to adapt to the epidemiological and demographic reality of a country and a set of parameters to describe the legal framework in that country. The focus of this article lies on the presentation of the model, but we also introduce a short illustrative example on how to use the model.

Contents

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1 Introduction

Countries around the globe are confronted with increasing costs of the their respective health care systems, while trying to provide the best possible care to their population. For instance, a recent opinion-poll in Switzerland found that the increasingly high costs for health care insurance represent the second highest concern of the Swiss population (Golder et al., 2018). Different policy measures to reduce costs or at least slow down the cost increase have been proposed in several countries. However, due to the complexity of the health care system and the importance of not putting at risk the quality of care, it is extremely difficult to predict the widespread consequences of such policy measures. The goal of this study is to present a first version of a computational model built to analyse the complexities of different health care systems.

The health care system is a highly complex system with a variety of actors such as health care providers, insurance companies, patients, pharmaceutical industries and the legislator. Different countries have different systems, but most of them face similar challenges: how to provide the best possible care at a reasonable cost and in a fair manner consistent with a country's values. Though health care systems around the world are very diverse, including national single-payer systems, completely privatised schemes, and mixed schemes, all of these systems are built around the dynamics that operate between the core actors of patients, providers, insurance companies and governments.

Recognising this common base to drastically different health contexts, we have developed a flexible model of the interactions between the core agents of a health system. The model can be adapted through parameters and input data to the rules and regulations of a specific national context. Thus the model can be contextualised to a wide range of health systems, without the creation from scratch of a new model.

With the creation of a flexible model of a health system, we aim to study *ex-ante* the effects of policy change in the area of health, which can impact outcomes in surprising ways due to the complexity of the interactions and dynamics within the system. The adaptive capability of agent-based models permit the analysis of far-reaching reforms, such as those recently implemented and proposed in the United States with the Affordable Care Act, as well as the proposals of several democratic candidates postulating for the 2020 elections. These reforms are challenging to study in traditional economic models, given that the analytic solution to a model depends on the structure of the context. In contrast, because the agents of agent-based models adapt to their changing context, structural change can be implemented as a policy experiment.

Another important reason for us to use an agent-based approach is the possibility of including demographic and epidemiological heterogeneity. This is crucial as we aim at adapting the model to different contexts and also because policy measures might have different effects for different individuals. We hope that this inclusion of heterogeneity coupled with the possibility of adapting the model to a specific context will enable this model to be a useful tool as virtual laboratory before any public policy proposal is actually implemented.

The purpose of this article is to provide a detailed description of *HealthSim* and a few illustrative examples on how the model works and how it can be used. In a parallel study, we carried out a fully-fledged policy analysis of a real policy proposal from Switzerland to illustrate the adaptation process of the model to a specific context (Chávez-Juárez et al., 2020b). In Section 2 we motivate the model through the importance of increasing health care expenditure and present the health care system seen from a complex systems perspective. In Section 3, we describe *HealthSim* in terms of its elements and process[1]. Finally, in Section 4 we illustrate through an example the model's capacity to analyse diverse outcomes how its elements can be adapted. The goal of this exercise is to analyse changes in the system, disregarding its particular context. In particular, some changes are analysed in relation to three parameters: income distribution, random seed and mandatory of health insurance.

2 Literature review: the complex health system

2.1 Relevance of health care expenditures (HCE) around the world

Although health systems are diverse around the world, many systems share similar problems. 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, 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 of individuals and governments that bear the burden of these costs.

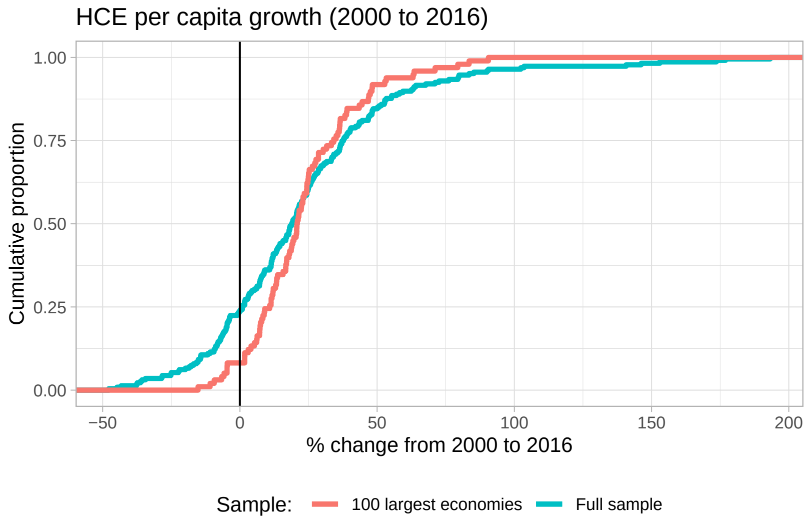
The large costs associated with many health systems are especially worrying because they are growing quickly. Average health spending per capita doubled from 2005 to 2015 among OECD countries (OECD, 2017), and these trends have not shown signs of slowing. Figure 1 plots the cumulative distribution of health care expenditure growth per capita, and shows that among the 100 largest economies, half of them had at least a 20% growth in expenditures per capita from 2000 to 2016.

Health care expenditures, however, are - and should not be - the only policy concern when dealing with the health care system. The quality of the health care system and in particular the quality of care is also a crucial aspect. Finally, the access to care and possible inequalities in the access to care add an additional layer of complexity and potential trade-offs for policy makers.

Both quality and universal access to care might suffer when the focus relies to heavily on reducing costs. The COVID-19 crisis in 2020 has shown that different health care systems might be more or less ready for a sharp increase in acute care cases and that both access to care during the crisis and the general health care status before the crisis might be unequally distributed in some cases (Ahmed et al., 2020). Hence, it is of paramount importance to have tools that can simultaneously focus on more than one key outcome.

[1] An even more detailed description of the model implementation can be found in the *Overview, design concepts and details (ODD)* protocol in Chávez-Juárez et al. (2020a)

Figure 1: Health care expenditure growth from 2000 to 2016



2.2 Complexity of the health system

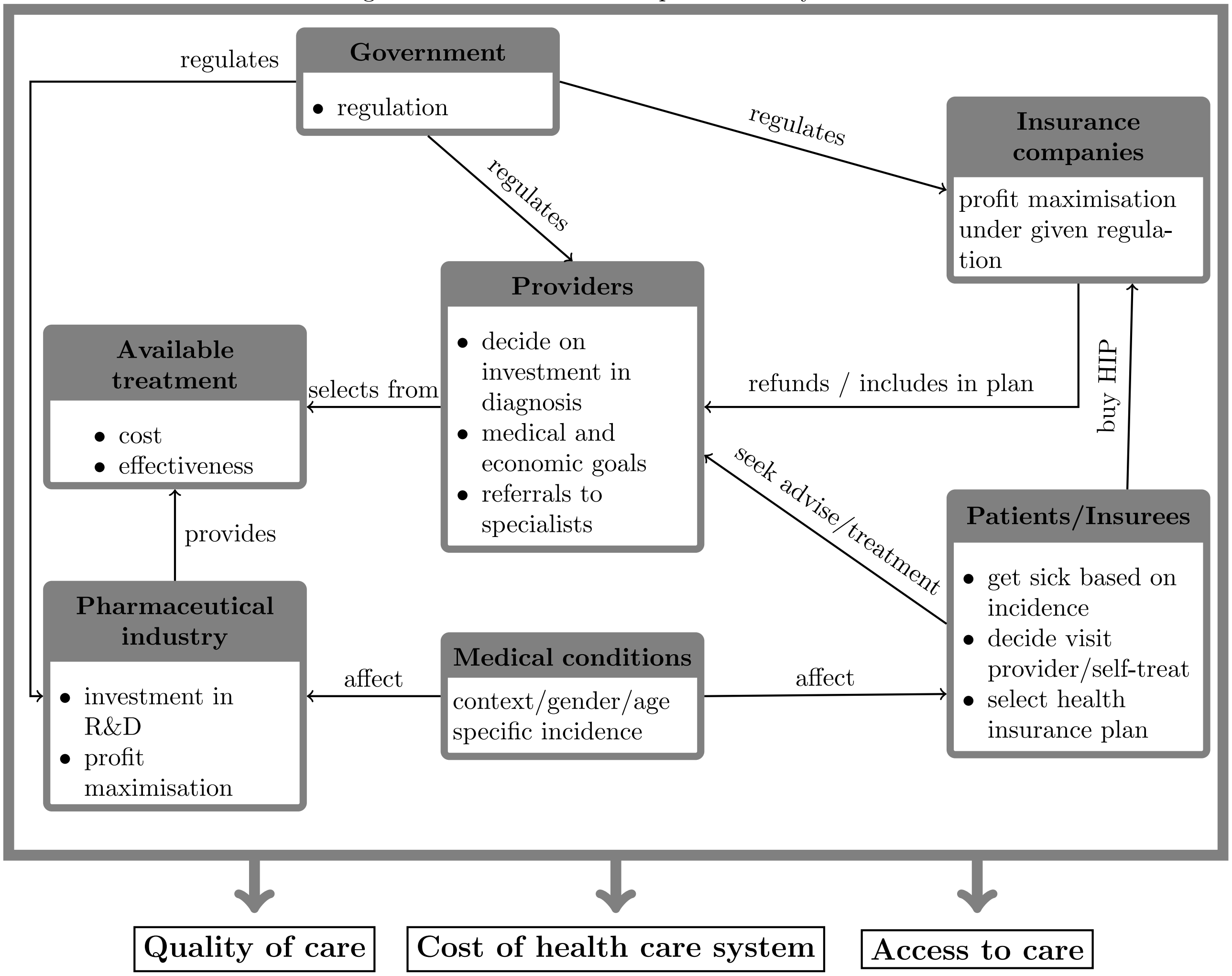
The common challenge that the health systems of many countries face despite their differences points to shared mechanisms at the micro-level that lead to potential inefficiencies. All health systems must deal with problems of moral hazard, provider incentives and the dynamics of insurance schemes, be it through markets or public provision. While the way that countries confront these issues and respond to the health needs of their population certainly vary, these complex dynamics between patients, providers, insurance companies and regulators lie at the heart of all health systems. It is the complexity of the interactions between diverse agents with different and often opposing objectives that generates inefficiencies, misalignment of incentives, and failed markets.

Figure 2 schematically illustrates the health system as we look at it. We identify five key actors in the system, namely the individuals/patients, health care providers, insurance companies, the pharmaceutical industry and the government. The figure additionally includes two boxes for illnesses and available treatments.

As we can quickly see from the figure, most actors have multiple links to other actors, making this a complex system. Moreover, in addition to the sheer number of interactions and relationships, the complexity is even higher when considering that within each box there are multiple players with not necessarily the same interests and roles. Most of the links we include in the graphic have been analysed and discussed individually in the health economics literature, but to the extent of our knowledge there is no model aiming at including all at the elements into a system with the purpose of analysing the system's behaviour as a whole.

Let us have a look at a number of relationships. The relationship between patients and insurance companies has been analysed extensively both theoretically and empirically. These efforts have focused mainly on issues like *moral hazard* (Manning et al., 1987; Rosett and Huang, 1973; Phelps and Newhouse, 1972), *cream skimming* (Newhouse, 1984) and *adverse selection* (Geruso and Layton, 2017; Cheng et al., 2015). Remedies to these problems include cost-sharing mechanisms to reduce the risk of moral hazard, mandatory insurance for residents to tackle adverse selection problems and regulation on insurance companies (e.g. mandatory

Figure 2: Scheme of the complex health system



acceptance of requests) to reduce problems of cream skimming.

The relationship between the health care provider and patients is no less complicated. Again, issues of asymmetric information make the relationship more difficult to analyse. For instance, under the assumption of positive marginal gains from treatment for providers and asymmetric information regarding medical needs, providers might be inclined to over-provide care through *supplier induced demand* (Evans, 1974; Johnson and Rehavi, 2016). A possible measure against such practices would be that insurance companies could stop collaborating with providers that charge above a certain suspicious threshold. However, such policy measures will have consequences all over the health system. One risk would be that in fear of being excluded from an insurance company and consequently from a pool of patients, providers could try to under-provide care. On the other hand, providers with higher costs (e.g.providers in peripheral areas) could be wrongly identified as over-providers and loose access to the system. This can then have consequences for the access to care of parts of the population.

Every health system has its particularities and in some systems some of the above issues might not be present (e.g. cream-skimming in a public health-insurance model such as the NHS in the UK). Nevertheless, the general mechanisms are very likely to be similar, yet not identical. In recognition of these shared dynamics, our model proposes a common framework for modelling the interactions at the micro-level. The present model focuses on the interaction between agents in the health system, with the hypothesis that while the rules under which agents operate may vary, the underlying objectives of the agents are shared. Patients seek to receive treatment for medical conditions, insurance companies interact with patients with the objective of economic gain (when permitted) and providers are motivated by medical and economic success. We mould the context of these interactions to a specific country's health system by adapting the rules under which these agents operate in order to mimic the relevant context. These rules can include, but are not limited to, regulation of insurance companies and their objective (for example, whether insurance companies can make a profit or fix rates optimally), the remuneration of health care providers, and whether or not patients can opt-out of insurance.

3 Model

In this section we present the first version of *HealthSim*. The methodology of agent-based modelling allows us to model the actions and interactions between autonomous agents in a simulated environment and assess their effects on the health care system as a whole. This model is built around three key agents in the health care sector: providers, health insurance structures and patients, all of whom can interact and adapt to their (changing) context and to other agents' decisions. In this section we provide an overview of the context and agents of this model, leaving the technical and mathematical details to the ODD presented in Chávez-Juárez et al. (2020a)[2].

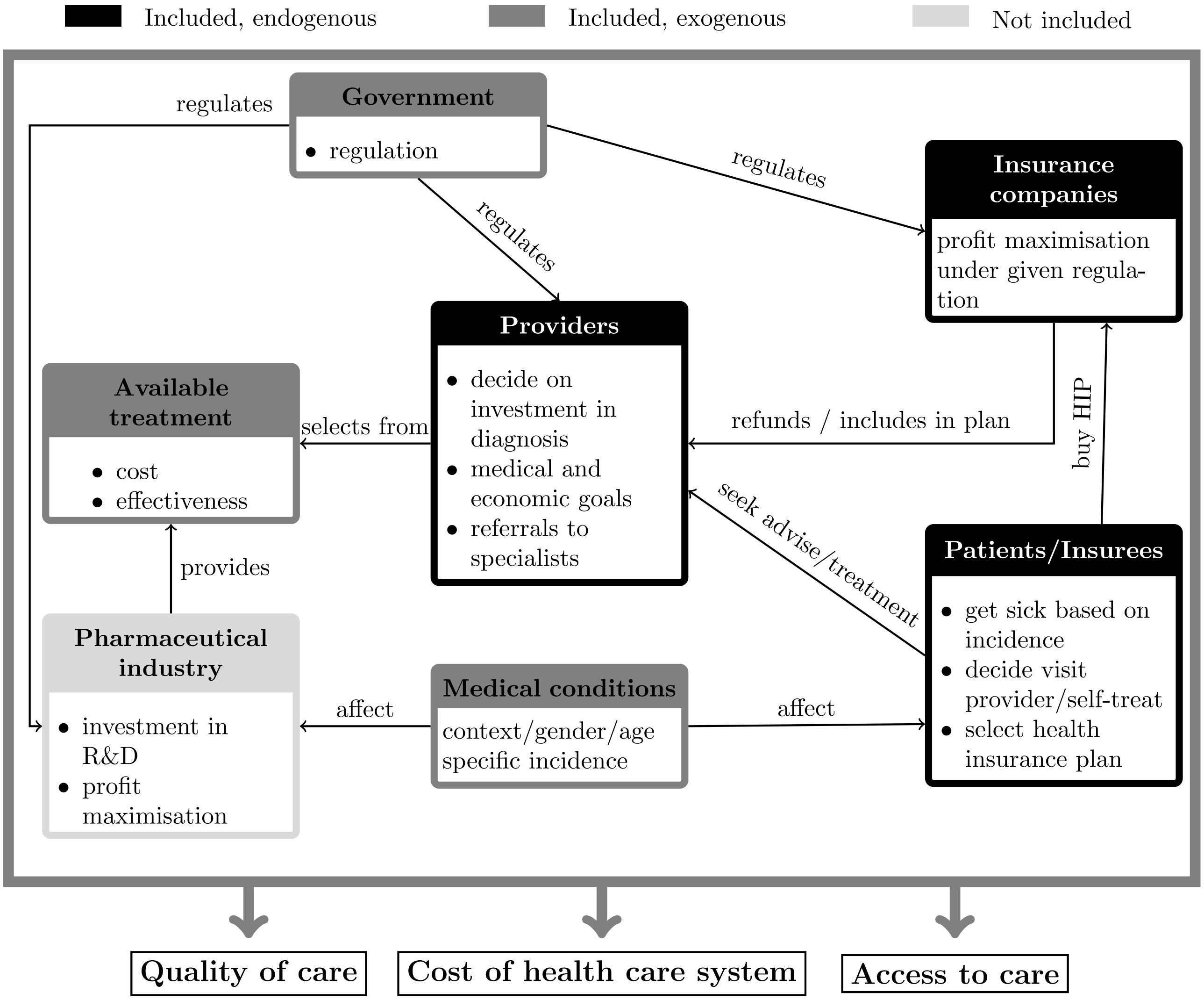
Before entering into the details, let us reconsider Figure 2 where we represent the whole health care system. In Figure 3 we present the same scheme, but this time referring to the current version of our model.

The black boxes refer to actors we have fully implemented with endogenous decision making. The dark grey blocks are implemented, but only exogenously. Here we basically have a set of parameters to exogenously describe the current regulation (i.e. government) and a series of input data to describe the incidences of a set of illness in the given context. Finally, the light grey block (pharmaceutical industry) is not yet implemented.

Our model is built on discrete time, where each period corresponds to one week. In every period patients get sick according to a context specifically calibrated epidemiological profile. Each medical condition has specific characteristics such as the initial severity and the progression if untreated. People then compute their willingness-to-pay based on the cumulative severity of their untreated medical conditions and its evolution to decide whether or not to visit a doctor by comparing their willingness-to-pay with the expected cost. The expected cost will depend on previous health care expenditure and can be high if the individual did not yet reach the deductible. Once the patient decides to visit a general practitioner, the GP invests in diagnostics and correctly identifies the medical condition with a given endogenous probability. If a treatment is available, it is prescribed, otherwise the patient is referred to a specialist. Insurance companies pay the medical treatments and the appointments according to the health insurance plans. These processes are

[2] The Overview, Design concepts, and Details (ODD) protocol (Grimm et al., 2006) provides a standardised and detailed procedure for documenting Agent-based models.

Figure 3: Scheme of the model



described in greater detail by type of agent in the following sections.

3.1 Context and Data

Our model is flexible and can be easily adapted to diverse socioeconomic and legal contexts. This is done through the modification of some system-wide parameters, such as whether or not insurance companies can engage in price discrimination based on health status, as well as through the importation of context-specific data on income, population structure, epidemiological distribution (incidences of selected illness), profiles of insurance companies, deductible levels of health insurances, costs of treatments and premiums.

Flexibility was a key tenant followed in the construction of the model, and the application of the model to a specific context is accomplished through the setting of parameters that control the structure of the model. These parameters allow the model to be tailored to the context of interest, be it a national public system, such as Canada or the United Kingdom, a fully privatised system, such as Singapore, or a mixed system, such as the United States. Parameters also control the permitted behaviour of insurance companies, determining what information they can use to set rates, what gate-keeping (if any) mechanisms they can employ, and whether they are profit-maximising or not.

Parameters also allow us to modify restrictions on patient behaviour: whether patients may opt-out of insurance or not is easily adapted to the case at hand.

Context-specificity is also accomplished through the importation of local disease, population and cost data that calibrates the model to a specific health system. There are two types of data imported into the model: data that are used to initialise the model, but that is later taken over by endogenous processes, and data that is imported into the model and that remains exogenous throughout the duration of the model.

Table 1 provides an overview of the endogenous and exogenous elements of our model.

Table 1: Overview of endogenous and exogenous elements of the model

Concept/element	**Exog.**	**Exog. → endog.**	**Endog.**
Health insurance			
- structure and rules	x		
- premiums		x	
Patients			
- disposable income	x		
- wealth			x
- health status			x
- health expenditures			x
- selected insurance plan			x
System statistics			
- mortality by age			x
- expenditures by disease			x
- distribution of used treatments			x
- age distribution of the population		x	
- causes of death			x
- number of consultations			x
- treatment availability and their unit costs	x		
Providers			
- consultation price	x		
- investment in diagnosis			x
- objective function parameters	x		

Exog. refers to exogenous elements that remain exogenous throughout the simulation. *Exog. → endog.* are processes that are exogenously set upon initialisation but then taken over by endogenous processes and *Endog.* refers to processes that are always endogenous.

Data that remain exogenous throughout the model include disease incidence and progression, disposable income, and the cost of treatments. Because we do not focus on preventive medicine in this version of the model, disease incidence is assumed to be unaffected by the processes of the model. Likewise, disease severity and progression remain exogenous throughout the model. Treatment costs (and their efficiency) are also assumed to be static[3], but the election of treatments (expensive vs. economical) is endogenous, and therefore

[3] In a future version of the model, we plan to introduce the pharmaceutical industry as an agent.

the contribution of treatment costs to the total of system costs is endogenous. Finally, the patients receive an exogenous endowment of disposable income based on the local income distribution. Though a patient's wealth will inevitably vary with their medical costs, we abstract away from the labour market consequences of health status in order to focus on the interaction of socioeconomic status on access to health care.

Other data are used to initialise the model, but after initialisation become endogenously determined. These data include the age distribution and insurance plan premiums. The model initialises with a population of patients whose age is drawn from a distribution of age that approximates the age distribution of the context at hand. However, because ageing and death is a product of the endogenous health status of patients, the evolution of this distribution is an endogenous process of the model. To keep the simulation population stable we replace each dying agent by an identical young agent. Similarly, we import initial insurance premiums as a sample of premiums available in the country being studied, but insurance companies modify these premiums endogenously based on average costs and the relevant regulation.

3.2 Patients

Patients receive exogenous incomes and face incidence of a country-specific disease portfolio according to the imported data outlined in the previous section. Given their income and health status, the patient faces two key decisions: optimise their health insurance portfolio and determine when to visit a health care provider.

First, patients optimise their health insurance portfolio by choosing between health insurance plans available to their age and sex category. These contracts last one year, at which point patients return to the insurance market and choose among available plans. Patients seek to insure themselves against a potential total annual health expenditure, which they estimate as a weighted average of their personal historical expenditures and a "worst-case scenario" (proxied by the 95^{th} percentile of expenditures by their peers), where the weight is their individual risk aversion. The model allows for transaction costs making the insurance plan change more expensive.

In each period (tick) of the model, the Patient gets sick with a disease-specific probability and severity. They then compute their willingness to way for medical services based on the cumulative severity their medical conditions, its recent evolution and their income. If they trust their family doctor and their willingness to pay is above the expected cost of the visit (taking into consideration what their insurance plan will reimburse), then they seek medical attention from the family doctor. Otherwise, they search for a doctor whose cost is below their willingness to pay. In the absence of one, they seek self-treatment. In this version of the model, we assume that Patients fully comply with treatments recommended by the doctor and with recommended follow-up appointments with specialists whenever they can afford to. The methods that define the doctor-patient interaction, diagnosis and recommendations are discussed further in the description of Providers in 3.3.

3.3 Health care providers

Health care providers seek to maximise their objective function, which depends on both economic and medical success (measured in share of correct diagnosis). This function gives varying weight to economic benefit vs. medical success and providers learn over time which level maximise their utility. For this learning process we use a PID controller[4] to achieve a high level of flexibility in the model. Health care providers can affect their direct economic benefit by increasing the amount of diagnostics used to identify the illness and through marginal benefits of some treatments. Increasing the amount of diagnostics also increases the likelihood of a correct diagnosis, but at the same time it might make the provider less attractive to patients because his overall cost rises. Of course, the exact trade-offs depend on the context. For instance, if the system is based on a fee-for-service scheme, over-investment in diagnostics might be economically interesting for providers, while the opposite is true under a DRG scheme. Hence, the learning process that agents engage in (through the PID controller) is interesting as it also allows us to simulate changes to the payment scheme and analyse how providers adapt their strategy.

Chronologically, the processes are implemented as follows. When health care providers receive a patient, they first decide how much they will invest in diagnostics based on their particular importance of medical success and on the severity of the patient's combined medical conditions. The probability of correctly detecting the patient's illness is determined by this investment in diagnostics, as well as the provider's skill level and the number of simultaneous medical conditions. If they correctly diagnose the medical condition and a treatment is available to the general practitioner, then they prescribe that treatment. For correctly identified medical conditions requiring medical care from a specialists, patients are referred to a specialist. Finally, if the GP does not correctly diagnose the medical condition, the patients will stay for at least a period without treatment.

At the end of each period, the Provider assesses the outcome of their objective function. Based on their success in the period as compared to the last period, the Provider adjusts their marginal investment in diagnosis accordingly through the PID controller.

3.4 Insurance companies

Health insurance organisations operate subject to the relevant legal context, which may dictate which types of plans they can offer and under what terms, whether they can make a profit or not, and how many operate in the model. Given these restrictions, Insurance Companies adapt their premiums either by using a learning algorithm (PID controller) or a simple cost covering algorithm. For example, where insurance companies are permitted to make profit, they will adapt premiums to maximise profit. In contexts where profits must be zero, insurance companies set premiums so that expected costs are equal to expected revenues.

In the current version the only endogenous behaviour of insurance companies is the selection of patients (when the system allows not to accept applicants) and the adaptation of the premiums. In contrast, the structure of health insurance plans or any type of innovation in the design of these plans are currently not implemented.

3.5 ABM advantages: learning and non-rational behaviour

Before moving to the illustration, let us briefly highlight some key advantages of our agent-based approach for the modelling of the health system.

[4] Proportional–integral–derivative (PID) controllers are popular in industrial control settings, and generate incremental movements towards a goal based on the last movement's changes towards or away from this goal. For a precise definition see the ODD.

Agent-based models permit the possibility of endogenous learning of agents. We implement learning in all of our agents; Patients learn about Provider quality and can switch providers if they have bad experiences, Providers learn through trial-and-error how much to invest in diagnostics in order to optimise their objective function, and Insurance Companies learn what premiums to charge to maximise profit. Though learning can be an interesting economic process in itself, learning is particularly important in the model because it permits agents to adapt to whatever context they face. It is learning, together with paramaterised or imported context variables, that permits agents to adapt to almost any policy change, far-reaching as it may be.

For an illustration of how adaptation allows the model to test policy change, consider a policy intervention that has been proposed in Switzerland: permitting insurance companies to exclude certain providers from their policies if these tend to bill high amounts (whether in consultation prices or diagnostic tests). Each agent in the model would adapt endogenously to this change. Insurance companies would exclude providers based on their billing, and providers learn and adapt their investment in diagnostics to the threat of exclusion. Finally, patients would adapt their demand for health insurance based on the new cost levels that they face in the market. In this fashion, the entire system can adapt to the regulatory change without changing the mechanics of the model.

Additionally, because agent-based models permit flexibility in the rules that agents follow in their decision-making, we are not limited to purely rational or optimal behaviour in the model. This allows the model to incorporate a wide array of literature in the rules that the agents follow, including empirical studies that observe "non-rational" decisions and research in psychology and behavioural economics. For example, we define an ad-hoc function for determining the amount of health expenditures that Patients want to be insured against by combining rational expectations of expenditures with a type of minimax strategy, which has been observed to be a common strategy employed in purchasing insurance in experiments (Kairies-Schwarz et al., 2014).

4 Simulation results

The model presented in section 3 is complex and therefore its presentation is challenging. In this study we focus essentially on the technical presentation of the model and abstract from the calibration exercise to adjust the model to a specific real-world context. A detailed exercise of adapting the model to a real-world context and analysing a real-world policy proposal is presented in Chávez-Juárez et al. (2020b), where we analyse the effects of changes to the minimum deductible levels in the Swiss Social Health-insurance market. In this study we borrow a simplified epidemiological profile from the Swiss paper and use very simple population settings. This simplification allows us to focus on the description of how the model works under different assumption. On the one hand we illustrate how different policies could be compared to each other and on the other hand we also discuss to what extent the model depends on or not on initial conditions and random elements.

This type of exercise is important due to the complexity of the model: changes in some parts of the model can produce unexpected outcomes. Therefore, it is highly relevant to understand how certain changes can affect other results and to test the model with different parameter settings. Simulations of this type can also be useful when there is little or no data on a specific context.

A question of this type may be, for example, how the existence of compulsory insurance affects the health status of a population and inequality within it. It is possible to use the model to answer this question without having to adapt it to a particular context. Furthermore, when exploring the same question for a specific context, it may be useful to have this abstract result as a reference.

We proceed by first presenting the simulation setup in subsection 4.1, then we present a policy exercise in subsection 4.2 and finish the section with a sensitivity analysis of the model in subsection 4.3.

4.1 Simulation setup

We test the model's results under different random seeds and parameters that control the characteristics of the simulated population and the regulatory environment. This allows us to analyse the effects of a policy reform under different population contexts. Specifically, we vary the population by experimenting with four mean preserving income distributions. For each income distribution, 4 different combinations of policy settings are used. These combinations come from two types of policy variation: whether purchasing insurance is mandatory or not, and whether or not insurance companies are allowed to price discriminate by age. We run the model with all combinations of the following parameter values (16 simulations total):

- 4 Income distributions: Uniform[900,1100], Uniform[750,1250], Uniform[500,1500], Uniform[1500,2500]
- 2 rules on mandatory insurance: Yes, No
- 2 rules on supply of insurance plans: All plans are open to all ages ("Pooled plans") and plans are offered to specific age groups ("Plans separated by age")

The last two parameter changes can be seen as a type of decontextualised policy experiment, which serve to illustrate the policy analysis that the model can do and to verify that endogenous mechanisms of the model produce coherent results. In one experiment, we compare the model's predictions under a mandatory insurance scheme as compared with a non–mandatory schemes. Similarly, we compare the model's predictions under two types of market segmentation by insurance companies. One, in which companies must offer all plans to all patients; we call this the "Pooled plans" scenario in the following graphs and analysis. This simulation is contrasted with the "Plans separated by age" scenario, in which insurance companies are allowed to segment their market by age group and price plan premiums differently by age.

Our simulation is carried out with 6000 individuals (patients) and we simulate roughly 20 years (or 1040 ticks) of our model. Due to some slow processes such as the adaptation of the premium prices to the actual costs generated in the model, we exclude the first 10 years of the simulation from all analysis to avoid depending on initial conditions. In preliminary runs we analysed how much time the model needs to stabilise and we decided that using results starting in year 10 are no longer depending on the initial conditions. In most cases the model stabilised much before that.

All simulations are carried out with a simplified epidemiological profile based on the one we used in (Chávez-Juárez et al., 2020b). We only include the following illnesses:

- **Cancer**: Severe chronic disease with a slowly increasing severity if untreated.
- **Influenza**: Typically a short-term non-chronic disease that does not necessarily require medical assistance.

- **Heart attack**: Very severe non-chronic disease requiring emergency response.
- **Osteoarthritis**: Chronic disease with slowly increasing severity. Treatments can only slow down progression.
- **Pneumonia**: More sever short-term non-chronic disease requiring medical assistance.

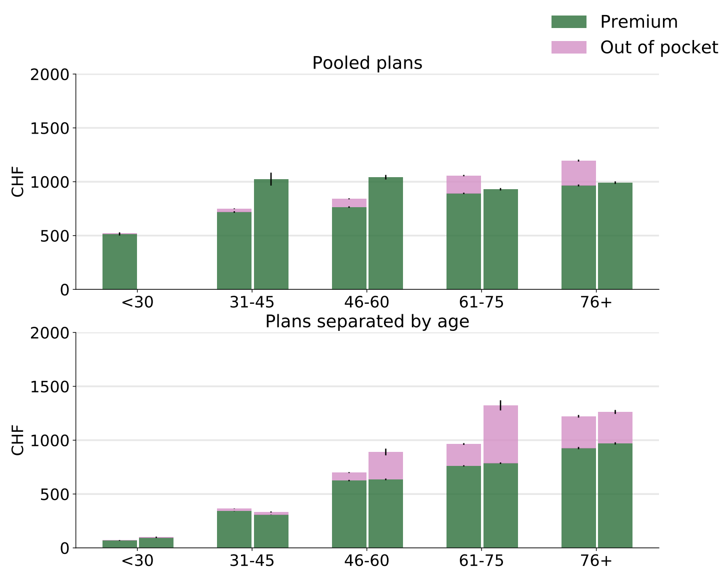
The selection of only 5 diseases was made to simplify the model as much as possible and to be able to focus on the presentation of the model, rather than a long epidemiological profile. As compared to the much longer profile used in Chávez-Juárez et al. (2020b), we selected diseases with different levels of severity and different time horizons.

4.2 Policy analysis

We now proceed to analyse the effects of changing the model's parameters in two dimensions related to the legal context of a health system: the mandatory vs. non–mandatory nature of contracting insurance, and whether or not insurance companies are allowed to segment the population and price discriminate by age.

In Figure 4, we see the total amount spent by patients on average in a year by age group. Total spending is composed of two main categories: annual spending on the insurance premium, and out-of-pocket expenditures composed of patient cost sharing and spending on self medication. In the Figure, in both panels and in each age category the bar to the right represents results when insurance is not mandatory, while its counterpart on the left corresponds to mandatory insurance. The top panel represents the scenario in which insurance companies are not permitted to price discriminate based on age, while in the bottom panel represents plans with pricing by age group.

Figure 4: Spending by age



Bars on the bars on the left correspond to mandatory insurance,
whereas bars on the right correspond to non-mandatory insurance.

In the pooled plans scenario, it can be observed that for individuals between 31 and 60 years old premiums are higher when when insurance is not mandatory (conditional on contracting insurance). This is consistent with economic theory, which predicts that when insurance is not mandatory, the highest–risk individuals will select into insurance, raising average claims and therefore premiums. For the youngest group in our analysis the difference is not visible because none of them selected into insurance coverage when it is not mandatory. This difference is hardly noticeable for older patients, possibly reflecting the lower variance in health needs in these age categories. It is interesting to note that these change is almost zero even for younger patients when plans are separated by age (lower panel): when premiums are set by age, younger patients have access to lower premiums, and overall represent a lower risk category for insurance companies. In this scenario, price discrimination also results in a much more pronounced increase in average premiums with age: while with pooled plans there is a slight increase in premiums with age, this slope is much more evident when plans are separated by age.

In Figure 5 the same structure is used to compare these scenarios but now using total patient spending as a percent of income by quintil. At a glance it becomes apparent that the poor spend a much higher percent of their income on health expenditures, with this proportion decreasing almost linearly with income. This reflects the fact that using the income levels chosen for this exercises, there is no real liquidity restraint in terms of accessing care in this simulation. Therefore, the poor spend about as much as the rich, but this represents a greater share of their income. In reality, this reflects the greater burden that health care expenditures represent for the poor, which in some cases may be subject to liquidity constraints.

Another important element to assess, as it could show inequities in terms of health, is life expectancy. We analysed this indicator for different socioeconomic levels and varying the parameter of compulsory health insurance. We did not find a conclusive differences under the two scenarios, but as we show in figure 6, life expectancies are slightly more homogeneous from 62.5 years old onward in the case where insurance is compulsory.

When comparing results between scenarios, one can see that in the case of pooled plans, making insurance mandatory reduces expenditures as a percent of income for all income groups. However, because this change appears to be proportionally beneficial for each group, there is no re-distributive effect of the policy. In the case of plans separated by age, there is no real income effect for patients, since separating plans by age makes the differences in risk created by forcing individuals who otherwise would not choose to purchase insurance to do so are minimal.

This illustration of the model's capacity to compare different policy scenarios is brief but shows some of the advantages of using this agent–based model to compare policy proposals. First is the level of detail that can be used; because the model exports data by tick and per person, the simulation can be analysed by income level, age, gender or health status to examine heterogeneous effects that may result for different segments of the population. This analysis focused on total patient expenditure as the primary outcome of interest, but the model can also be used to analyse outcomes such as appointments and health status, which may be important measures of quality of care and access to it for policy makers.

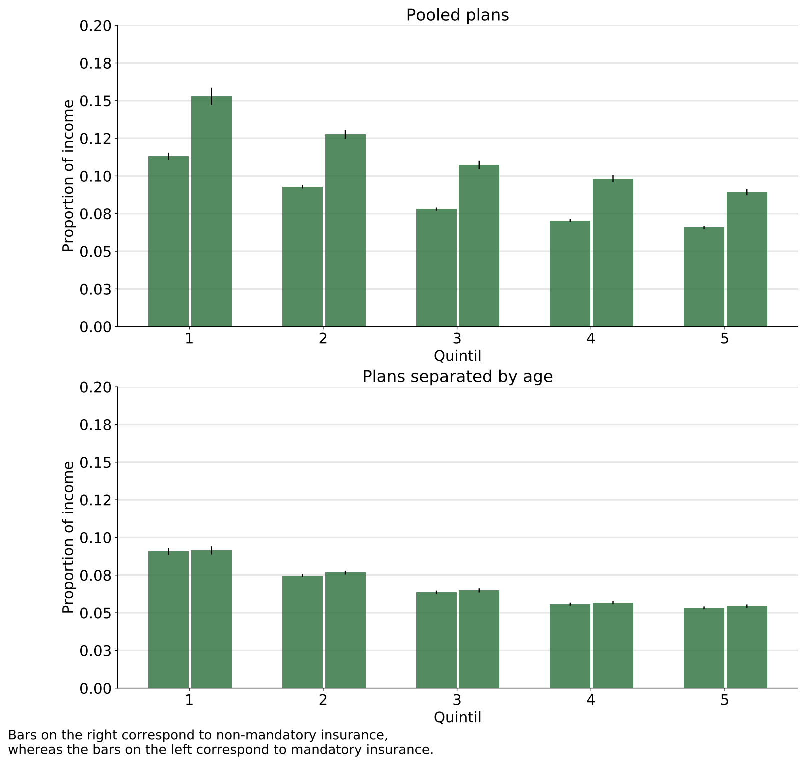


Figure 5: Spending by quintil as percent of income

4.3 Sensitivity analysis of the model

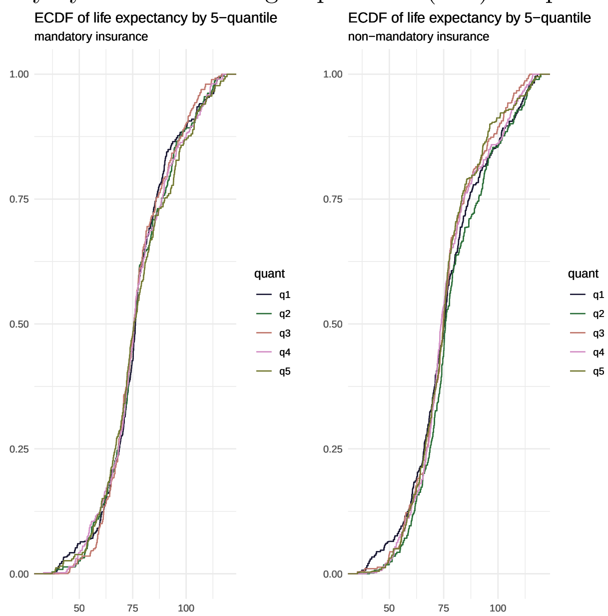
Currently under revision

5 Conclusions

The goal of this article is to introduce *HealthSim*, a flexible agent-based model of the health system. The detailed description of the model should allow reader to understand the basic mechanisms on which the model is based, for all the technical details we refer to Chávez-Juárez et al. (2020a).

Given the complexity of health systems, the use of agent-based models is one way of analysing potential policy effects. We particularly emphasise on the need of analysing multiple outcomes such as the average HCE, the access to care and the quality of care. The need for this multi-goal approach has been highlighted during the COVID-19 crisis in 2020. Before the crisis the increase in cost of the health care system dominated the public policy debate. During the crises outcomes such as the general quality of care and particularly the equality in the access to care regained importance in the public debate.

Figure 6: Life Expectancy by socioeconomic groups under (non) compulsory insurance scenarios



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