HealthSim - ODD protocol

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Abstract

This document presents the Overview, Design Concepts and Details (ODD) protocol for the *HealthSim* model. We additionally also present a short section with a summary of variables, parameters and indices used in the model.

This document is constantly being updated.
You always find the newest version at:
`https://github.com/fwchj/HealthSim`

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1 Overview

1.1 Purpose

The goal of this model is to model the health care system comprehensively considering its complexity due to the large number of players. The goal of this general model is to provide a baseline model from which more context (e.g. country) specific models can be developed through small adaptations. In this sense, the model aims at being very general to accommodate different types of health care systems.

1.2 State variables and scales

The model structure is relatively complex and many auxiliary variables are used in the code. Table 1 highlights the most important state variables along with a number of important auxiliary variables. Some other auxiliary variables are omitted as they are not required to the replication of the model.

Table 1: State variables and scales

State variable	**Scale**
Patients	
- Age	[0,∞]
- Female	True/False
- Health status	[0,1]
- Health expenditures	$[0, \infty]$
- Wealth	$[-\infty, \infty]$
- Medical conditions	Array of medical conditions
- Health insurance	Array of insurance plans
- FamilyDoctor	Provider: the current family doctor (can be empty)
- Trust	This is key-value combination for each provider: <Provider,[0,1]>
- riskAversion	[0,1]
Providers	
- Diagnosis investment (δ_0, δ_1)	$[0, \infty]$
- Quality of provider	[0,1]
- fixedCosts	[0,∞]
- capital	$[-\infty, \infty]$
- specialist	True/False
- capacity	Capacity of patients per week [0,∞]
- alpha (α)	Parameter of objective function
- Profit	$[0, \infty]$
- Share correct diagnosis	[0,1]
Insurance Companies	
- Health insurance plans	Array containing health insurance plans including their premiums, age groups, etc.
- Profit	$[-\infty, \infty]$
- Reimbursements	$[0, \infty]$
Health insurance plans	
- Insurance company	Link to offering insurance company
- Premium	$[0, \infty]$
- minAge	$[0, \infty]$

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Table 1 – continued from previous page

State variable	**Scale**
- maxAge	$[minAge, \infty]$
- womenAllowed	Boolean to indicate if women can contract this insurance plan
- menAllowed	Boolean to indicate if men can contract this insurance plan
- deductible	Level of the annual deductible: $[minAge, \infty]$
- copaymentRate	Level of the copayment rate: percentage
- stopLoss	Level of the stopLoss (if applicable)
- stopClaim	Level of the stopClaim (if applicable)
Illnesses	
- name	Name of the illness (string)
- contagious	Boolean for contagious diseases
- chronical	Boolean for chronical diseases
- betas	Set of estimated parameters used for the conditional probability of having this illness
- treatments	Array of available treatments
- initialSeverity	Severity level when disease starts
- deltaSeverityWoTreatment	Weekly change in severity if untreated $[-1, 1]$
- genDiagnosis	Boolean to indicate if illness can be detected by a GP
- probabilityDetection	Set of parameters to describe the probability of detection
- emergency	Boolean to indicate if it is a emergency (e.g. Stroke)
Medical condition	
- Illness	Link to the illness
- initialTick	Initial tick of the medical condition
- treatment	Link to current treatment
- severity	Current severity of the medical condtion
- wasTreated	Boolean for having received a treatment

1.3 Process overview and scheduling

Table 2: Overview of processes

Priority	Agent	Method and processes
100	Model	**stepResetModel()** 1. Resets the incidence counter to zero for each illness 2. Resets the prevalence counter to zero for each illness, only every 52 ticks (each year)
99	Patient	**stepResetPatient()** 1. Resets the following values: expectedOOPExp (0), visits (null), OOPExp (0), wtp (0) HS (current health status), capital (+=income; if indebted debt increases by interest rate), age(+1) 2. Checks if agent dies. If yes, agent is removed from the simulation, and a new identical agent with the minimum age is added. The health status is randomly drawn, but characteristics (e.g. tolerance to pain, location) are identical to the defunct individual. 3. If not dead: removes all the medical conditions with a severity of zero (cured)
98	Provider	**stepResetProvider()** 1. Update of instance variables: capital (+=income), income (0), number of appointments (0)
95	InsuranceCompany	**stepAdaptHIOffer() (every 52 ticks)** 1. PID controller modifies insurance premiums to maximize profit
91	Model	**updateHCEexp()** 1. uses information of *logExpenditures*, compute statistics (mean, variance, percentile 95) and save data for each age-gender group in HCE.

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Table 2 – continued from previous page

Priority	Agent	Method and processes
90	Patient	**stepContractInsurance() - only every 52 ticks** 1. Patient selects among the actual offer of affordable HI plans 2. If the patient finds a HI, the health insurance is added and the premium is paid upfront (adding to the insurer's list of active plans).
80	Patient	**stepGetSick()** 1. With a certain probability (depending on the characteristics), new medical conditions are added to the patient
70	Patient	**stepGetMedicalCare()** 1. The patient computes perceived medical needs and willingness to pay for medical care 2. Patients decide whether or not to visit a Provider 3. Patients decide which Provider they will visit based on trust, willingness and ability to pay. 4. If they don't find a Provider, they search for affordable self treatment. If able and willing to pay, they pay for and apply self treatment. 5. If they do find a Provider, the Provider analyses Patient and Patient pays Provider. Patient's income, health care expenditure log are updated. 6. Patient gets reimbursed by insurance company. 7. Patients get treated, and their MedicalCondition(s) get better if treated correctly or worsen if not.
2	Provider	**stepUpdateParameters()** 1. Update Provider's "profit" history with the result of the objective function from the last tick 2. Adapt base level of diagnostics using PID controler.

2 Design concepts

2.1 Basic principles

This model is based on a variety of basic principals. The parts of the model related to economic behaviour is based on general health economics research with a particular focus on behavioural economics. The medical part of the model is not directly based on a basic principal but rather the fruit of discussion with medical experts such as medical doctors.

2.2 Emergence

In this model a variety of phenomena emerge from the model:

- Provider behaviour with respect to the investment in diagnostics
- Age, wealth, health status distribution of the population
- Cost structure of the health system
- Price structure of the health insurance market

2.3 Adaptation

A number of agents adapt their behaviour in the model:

- Providers
  - Providers adapt their diagnostics (amount) through a learning process where they aim at maximising their objective function.
- Patients
  - Patients adapt their decision to enter the health care system (seek care) depending on their economic and medical situation
  - Patients also adapt (i.e. change) their family doctor in function of previous experiences
- Insurance companies
  - Insurance companies adapt to the insurance market and the regulation by adapting the price structure of their products.

2.4 Objectives

Each type of agent has different objectives, except for the government, which is implemented in a passive way without explicit objective.

Patients

The goal of patients is to live a healthy life (by maximising their health status) at a reasonable price. Hence, patients evaluate the cost of seeking care and getting treated against its cost.

Providers

Providers maximise their objective function (see eq. 12) which essentially depends on their medical success (measured as percentage of correct diagnoses) and their economic profit. We have a parameter for the relative strength of each of the two arguments. Hence, the model can easily accommodate a single variable objective (either health or economic). Providers optimise their objective function through a learning process.

Insurance companies
Insurance companies care essentially about maximising their economic profit within the legal framework of the context. We implement this through the maximisation of profitability of each of their health insurance plans and use a learning algorithm (PID controller). We do not allow insurance companies to try to maximise their profit outside the legal framework (i.e. they always comply with regulation).

2.5 Learning

Providers are currently the only agents learning in the model. They use a PID controller to learn their best combination of parameters to define the level of diagnostics they use for each patient. We use this kind of learning rather than a more structural approach here because this process is likely to change very strongly with the public policy in place.

2.6 Prediction

In our model we do not have an actual prediction of future outcomes *per se*. However, a few processes use information for the past to make decisions about the next period. For instance, patients use their past expenditures to forecast their future needs. Insurance companies and providers to something similar through the directional learning process we include in the model.

2.7 Sensing

In this model we try to model the information agents can use to take decision as closely as possible to reality. Agents do have access to some population statistics (e.g. an estimate of catastrophic costs of similar patients) and all that is directly observable to them. Insurance companies have no particular access to data of the patient, but can infer for instance the health status via the reimbursement requests of an agent.

2.8 Interaction

Interaction plays a crucial role in our model, both between patients and providers and patients and insurance companies. The current version does not explicitly include interaction between providers and insurance companies. Interactions with the regulator are all simple in the sense that our agents follow the regulation under all circumstances. The interaction between providers and patients is a multi-layer interaction, both passive and active. Providers passively interact with patients through their adjustments, which make patient more or less likely to chose a particular provider. The more direct interaction takes place whenever a patient decides to seek care and enters the health care system. As of this moment the interaction is direct through the process of the medical consultation and treatment.

2.9 Stochasticity

We have a multiplicity of stochastic elements in our model, therefore it is important to well distinguish those present only upon initialisation from those acting during the simulation.

Stochasticity upon initialisation

- Providers: location on the grid, the relative importance of economics vs. health outcomes (α), quality of the provider
- Patients: location on the grid, gender, income, age, risk aversion

Stochasticity during the simulation

- Providers: based on a computed probability, the provider correctly assesses the medical condition
- Patients: based on the age-gender dependent incidence data, patients become sick

2.10 Collectives

We do not have collectives in our model.

2.11 Observation

We collect information at different levels in each tick. For health insurance we export data at the company level, but also for each individual health insurance contract. These data have a time granularity of typically 52 weeks as they are purchases on an annual basis. Individual level data on health and economic related aspects of the individual are exported on a weekly (=tick) basis. The same holds true for providers and medical conditions. Due to the amount of data, much attention has been paid to minimise the amount of data, but still allowing to follow each patient and each of his/her medical conditional on a weekly basis by ex-post combining databases.

3 Details

3.1 Initialisation

In this section, we describe the type of variables using the terminology from programming, where we stick to the following rules:

- `Integer` integer value such as 1,2,3,4,99,etc. No decimals allowed
- `Double` decimal values, but you can also add an integer (example: 22.302)
- `String` text value with alpha-numeric values

Note that all values, especially the field names, are case sensitives.

3.1.1 Population

The population to initialise the model is based on summary statistics of the target population. For simplicity, we assume independence of characteristics, which allows us to use a series of uni-variate distributions rather than a more complicated multidimensional distribution. The following characteristics are initialised based on random draws from distributions.

age	Two-part function that simulates the age distribution (country specific).
income	Log-normal distribution calibrated with summary statistics of the target population. The idea is to get a good measure of the disposable income per capita.
gender	Random value with 50% probability for each gender

3.1.2 Illnesses, incidence and treatments

Illnesses, illness incidence and treatments are imported from a single Excel file `swiss_data` with three tabs for each of the elements:

- `illnesses` contains information on the different illnesses
- `treatments` contains information on the possible treatments
- `incidence` contains the incidence data for each illness and for different subgroups of the population

Illnesses are linked to treatments (1:m) through a unique alphanumeric identifier of the illness (field `illness`) present in both tables (tabs). The number of treatments `m` for each illness could be variable. Also illnesses are linked to incidence (1:2*p) through the identifier but `incidence` table should be in wide format (where the repeated observations for a given group are incidences for different illnesses). The number of age-groups, `p`, should be the same for all illnesses.

3.1.2.1 Illnesses [tab `illnesses`]

The tab `illnesses` should have a first row with the field names (order does not matter) and starting on row 2 the data should be put. Try to avoid empty cells. You can add additional columns (e.g. observations) as long as their field name (first row) does not match any of the above mentioned columns.

Field name	Type	Description
id	Integer	Unique numerical ID for each illness
illness	String	Name of illness
contagious	Double	Equal to 1 if the illness is contagious; 0 otherwise
chronic	Double	Equal to 1 if chronic; 0 otherwise
highPrevalence	Double	Equal to 1 if the disease is relatively prevalent in the context; 0 otherwise
highCost	Double	Equal to 1 if the disease imposes relatively high costs on the patient in the context; 0 otherwise
initialSeverity	Double	The initial severity of the illness; calculated as a function of the severity without treatment and how long it takes to become visible.
severityWoTreatment	Double	Change in the illness's severity in the absence of treatment
visibilitySymptoms	Integer	Number of weeks before the illness is detectable (currently this value is not used in the model)
probabilityDetection	Double	This is the baseline probability without any investment in diagnostics.
deltaProbDetectionInvest	Double	The probability increases by this amount per unit of investment in diagnostics.
probMaxDectection	Double	This value is the maximum value the probability can attain. The program limits this value automatically to 1.0, but it can be selected at a lower level of diseases that are hard to detect despite heavy investment in diagnostics.

3.1.2.2 Treatments [tab `treatments`]

The tab `treatments` should have a first row with the field names (order does not matter) and starting on row 2 the data should be put. Try to avoid empty cells. You can add additional rows (e.g. observations) as long as their field name (first row) does not match any of the above mentioned rows.

Field name	Type	Description
id	Integer	Unique numerical ID for each treatment
illness	String	Name of illness
description	String	Brief description of the treatment (wait, simple drugs, etc.)
cost	Double	Cost of treatment in context-specific prices
marginalBenefitProvider	Double	Proportion of the cost that goes to the Provider
deltaSeverity	Double	How much the treatment helps to cure the medical condition. Note that here we typically use negative values, given that a treatment should decrease the severity. For instance, if the treatment reduces severity by 0.05 each week, then the value of `-0.05` should appear in the data.
minSeverity	Double	Minimum severity of the medical condition to be eligible for this treatment
maxSeverity	Double	Maximum severity of the medical condition to be eligible for this treatment
type	Double	SELF, TREATMENT_NORMAL, TREATMENT_SPECIALIST

3.1.2.3 Incidence [tab `incidence`]

The tab `incidence` should have a first row with the field names (order does not matter) and the actual data should start on row 2 with no empty rows. Three columns to identify the subgroup of the population are mandatory and for each illness in the data (see tab `illnesses`) on additional column should be added. Empty cells should be avoided and non-available probabilities should be indicated with a negative value (e.g. -9.0). You can add additional columns (e.g. observations) as long as their field name (first row) does not match any of the above mentioned columns.

Field name	Type	Description
gender	String	Indicator for gender, possible values: `male`,`female`
age_start	Integer	Lower bound of the age range. Unit: years.
age_end	Integer	Upper bound of the age range. Unit: years.
Multiple	Double	For each illness one column should be added. The first row contains the alpha-numeric identifier of the illness and the remaining rows include the annual incidence for the given sub-group of the population. For instance, a value of 0.1 would suggest that a person of this gender-age-group has a 10% change of having this illness. Values above 1 are possible to indicate that these illnesses appear several times a year (e.g. common cold).

The following example used age groups of 10 to 15 years and only two illnesses. Note that for the youngest age-group no data is available and therefore the value -9 was used. You can actually use any value below zero.

```
gender   age_start   age_end   Asthma   Arthritis
male             0        14       -9          -9
male            15        24    0.054       0.001
male            25        34    0.041       0.021
male            35        44    0.039       0.037
⋮
male            75       130    0.044       0.257
female           0        14       -9          -9
female          15        24    0.077       0.012
⋮
```

3.1.3 Average health-care expenditures

To initiate the model we need information on the average annual health care expenditure by age and gender. To input this data, we use a single `csv` database with the field names on the first row and followed by the actual data. The file name must be `ExpHCE.csv` and the values must be comma-separated (not semi-colon). For this file it is important to keep the order of variables as displayed in the following tables.

Field name	Type	Description
age	Integer	The age of the individuals in years. If only information in age-brackets is available, a row per year should be added with the same values.
expHCE_women	Double	Average health care expenditures for women
expHCE_men	Double	Average health care expenditures for men

3.1.4 Health insurance companies and plans

All the data related to health insurance companies and their insurance portfolio are imported from a single Excel file `hi.xlsx` with two tabs on `insurers` and `hiplans`. The tab `insurers` includes information on the health insurance company, while the tab `hiplans` include information on each proposed health insurance plan.

3.1.4.1 Insurance companies [tab `insurers`]

The tab `insurers` should have a first row with the field names (order does not matter) and starting on row 2 the data should be put. Try to avoid empty cells.

Field name	Type	Description
id	Integer	This must be a **unique** identification number for each insurance company. In case of duplicates, the program might not work properly.
capital	Double	Initial capital of the health insurance company
profitTarget	Double	The target of the profit rate a firm has. See XXX for more details. For instance, if a 20% profit rate is targeted, the value of 0.2 should be used.

3.1.4.2 Health insurance plans [hiplans]

The tab `hiplans` should have a first row with the field names (order does not matter) and starting on row 2 the data should be put. Try to avoid empty cells.

Field name	Type	Description
id	Integer	This must be a **unique** identification number for each insurance plan. In case of duplicates, the program might not work properly.
insurer	Integer	ID of the insurance company. This must link to a unique id in the health insurance data. If the id of the insurance company is not found, the health insurance is ignored.
premium	Double	The initial premium charged to clients. This value might endogenously adjust during the simulation.
minAge	Integer	Minimum age for eligibility
maxAge	Integer	Maximum age for eligibility
deductible	Double	The amount of the deductible
copaymentRate	Double	Co-payment rate once the deductible is attained. For 5% put the value of 0.05.
stopLoss	Double	Amount of the stop-loss. If no stop-loss is present, put zero. This cannot be mixed with stopClaim.
stopClaim	Double	Amount of the stop-claim. If no stop-claim is present, put zero. This cannot be mixed with stopLoss
gender	String	String value to identify who can purchase the insurance: • `women`: Insurance is only available to women • `men`: Insurance is only available to men • `both`: Insurance is only available to both women and men

3.2 Input

During the simulation there are no changes of input parameters.

3.3 Submodel: patients

3.3.1 Choosing insurance plans

As buyers on the health insurance market, patients seek to purchase the most affordable health insurance offered to their age-gender cohort (if any) based on their subjective estimation of their future health expenditures. When the legal context permits, if no available plan is cheaper than their expected out of pocket expenditures, they do not purchase insurance.

We emphasise the subjective nature of expected health expenditures due to a vast literature that stresses that insurance buyers frequently follow strategies other than simple rational assessment of their expenditures when purchasing insurance. Cumulative Prospect Theory (Barseghyan et al., 2013) posits the over-weighting of extreme and unlikely events, and many of its implications are consistent with Regret theory (Braun and Muermann, 2004) and minimax strategies, which empirical studies have found to be common in insurance purchasers (Kairies-Schwarz et al., 2014).

In order to simplify these theories and avoid the imposition of a specific utility function, we posit a heuristic that the patient follows to estimate the amount of expenditures that they would like to insure. The patient takes a weighted average of their past expenditures (approximated with a linearly weighted moving average) and a catastrophic expenditure, estimated with the 95$^{\mathrm{th}}$ percentile of population expenditures within their age-gender cohort. This heuristic is summarised in Equation (1).

$$E[expen_{T,i}] = \omega_i \; max\{p95_{a,g},\; movav^{M}_{i,T}\} + (1-\omega_i) movav^{M}_{i,T}\;, \qquad \omega_i \in [0,1] \tag{1}$$

where $\mathrm{p95_{a,g}}$ is the 95$^{\mathrm{th}}$ percentile of health expenditures for age-group a and gender g, and $movav^{M}_{i,T}$ is the moving average of annual health expenditures from years *T-1* to *T-M* for individual i with weights decreasing linearly until 0 after memory *M*. We choose M such that the patient considers their expenditures from the last 5 years. The parameter ω_i represents the importance that an individual puts on insuring catastrophic events, and can be thought of as an approximation of their risk aversion. It is a random draw from a Beta distribution with $\alpha = 5$, $\beta = 1.5$, which gives an expected value of 0.77, a proportion close to the proportion of buyers using minimax strategies found in Kairies-Schwarz et al. (2014).

We assume that there is a cost associated to changing between health insurances between years. Therefore, each patient multiplies by a factor ζ the cost associated to each of the evaluated Health Insurance Plans that she did not hire last year. As a consequence, the Patient will rehire her Health Insurance Plan unless there is another plan with a considerably lower cost, depending on the value of ζ.

3.3.2 Decision to visit a health-care provider (first contact)

Our implementation on how agents decide whether or not to visit a doctor (first contact) is based on four key elements discussed in the literature. The **perceived medical** need positively affects the likelihood of visiting a health care provider. The **expected cost** negatively affects the probability while **income** positively affects it. Finally, we also include the notion of **tolerance to pain**, where individuals with a higher level of tolerance are less likely to visit a doctor, holding everything else constant.

We first discuss our implementation and once the implementation is explained, we refer to the literature and explain how our implementation respects the findings of the literature.

Perceived medical need

Let us first define the perceived medical need. Here the idea is that each individual i in period t has some knowledge about her health status. Individual i has a set M_{it} of medical conditions which we will index by the subscript m.

To determine the self-perceived medical needs we include two major elements. First, agents look at the deterioration of medical conditions and second, they consider their overall health status. Mathematically, we can define the level of needs as follows.

$$need_{it} = \underbrace{\left[\sum_{m \in M_{it}} S_m \times \frac{d_m}{d_m + 1} \times \mathbb{1}(S_{mt} \geq S_{m,t-1}) \right]}_{\text{severity of deteriorating conditions}} \times \underbrace{\left[\sum_{m \in M_{it}} S_{mt} \right]}_{\text{lack of health status}} \tag{2}$$

where S_m is the severity of medical condition m and $d_m = t - t_m^0$ refers to the time since the medical condition appeared for the first time. The first term of equation (2) captures all untreated medical conditions with weakly increasing severity. The severity can increase for two reasons. First, in the period when symptoms become visible the severity mechanically increases. Second, medical conditions that are not treated or wrongly treated might increase in severity. We multiply the severity by a factor of duration to capture the possibility that individuals do not go to the doctor upon the first signs of a medical condition but then decide to go when they persist. Note that this first term is not affected by medical conditions that are being successfully treated.

The second term is a measure of the overall lack of health, which is basically the sum of the severity of all medical conditions. The idea here is that given a positive value in the first term (deterioration), patients with an already low health status will consider the situation as more severe than a similar person with no other medical condition. As an illustration we could imagine a person with a severe chronic medical condition who is more likely to visit the doctor when having symptoms of influenza as compared to an otherwise perfectly healthy individual.

Willingness to pay

Once we have defined the perceived medical need, we now use this information to determine how much the individual is willing to pay. The basic idea is that the more medical needs and the more income an individual has, the more he or she is willing to spend. Let us define the general function as following:

$$wtp_{it} = f(needs - tolerance, capital) \equiv f(n, y) \tag{3}$$

where the willingness-to-pay (wtp) depends on the needs, a certain level of tolerance to pain and the disposable capital (income + savings). We make the following assumptions on the functional form:

Assumption	Justification
$f_n > 0$	The first derivative of the function with respect to *needs-tolerance* is positive, suggesting that people with more needs are willing to pay more for care.
$f_{nn} \geq 0$	The second derivative with respect to medical needs is expected to be (weakly) positive. Chuck et al. (2009) finds some evidence for this assumption.
$f_y > 0$	We expect income to have a positive effect on the willingness-to-pay in absolute terms.
$f_{yy} =?$	A priori, we do not want to impose any sign for the second derivative due to a lack of information in the literature. Bobinac et al. (2010) seems to find evidence both for concave and convex functions, depending on the socio-economic status. To keep the model as general as possible, we do not impose any restriction.
$f_{ny} \geq 0$	The cross derivative is very interesting, but unfortunately the literature does not provide many insights. Based on Vlaev et al. (2009) we suspect that it should be weakly positive.
f(0,y) = 0	For medical needs that are below the tolerance level of the individual, the willingness-to-pay is equal to zero. Note that n cannot be negative.

Based on these properties and with the goal of keeping the implementation as simple as possible, we propose the following functional form:

$$wtp_{it} = \gamma(n_{it} - t_i)^{\alpha} y_{it}^{\beta} \tag{4}$$

with $\alpha \geq 1$, $1 \geq \beta > 0$ and $\gamma > 0$. α captures the sensitivity of the willingness-to-pay with respect to the perceived medical needs, where we typically assume a value above unity. Tolerance is set to 0 in this first version of the model. β measures the sensitivity to income and γ is a simple scaling factor which we will calibrate with real-world data. Note that this implementation of *willingness-to-pay* refers to the process of receiving medical advise and does not include possible treatment costs. An advantage of this implementation is its neutrality to the units of income, hence the model can operate with different currencies.

Expected cost of doctor visit Before taking a decision, each individual estimates the expected cost of the doctor visit and compares this value to self-treatment.

$$\widehat{CT_{it}^{p}} = E\left[cost|HI_{it}, T, S_m, type = provider\right] \tag{5}$$

$$\widehat{CT_{it}^{self}} = E\left[cost|HI_{it}, T, S_m, type = selfcare\right] \tag{6}$$

Decision to visit the health care provider

Once the individual knows her willingness-to-pay and the two expected costs, the decision becomes straightforward:

$$action = \begin{cases} \text{visit family doctor} & \text{if } wtp_{it} > CT_{it}^{FD} \wedge trust_i FD > 0 \\ \text{visit other doctor} & \text{if } wtp_{it} > CT_{it}^{p*} \\ \text{self-medication} & \text{if } wtp_{it} < CT_{it}^{p} \wedge wtp_{it} > CT_{it}^{self} \\ \text{wait and see} & \text{otherwise} \end{cases} \tag{7}$$

where $p*$ is the best provider based on a mixed criterion of cost (below wtp_{it}) and the level of trust.

3.3.3 Our implementation related to the literature

Let us now briefly look at the whole process and relate it to the underlying literature. Notice that equation 2 considers indirectly the psychological factors proposed by Campbell and Roland (1996): *perceived severity of symptoms* as the equation runs only over medical conditions with symptoms; *perceived susceptibility and vulnerability to the disease*, because individual takes in account change in severity and total health status.

Perceived costs and perceived benefits are included through equation 3 where each individual computes his/her willingness to pay and through the computation of the expected cost.

Equation 2 includes another factor that has been highlighted by Campbell and Roland (1996) but also by Taber et al. (2014): the duration of a symptom. This duration is an important issue for the decision to visit doctor because some symptoms tend to disappear **by themselves** in days. In this sense, equation 2 is consistent with Campbell and Roland (1996) symptoms, *needs* in the model, are highly perceived when symptoms do not disappear over time (and some illnesses could decrease its severity by its own). Equation 3 takes into consideration the severity hypothesis, stated by Richardson et al. (2017), but extrapolated for individual willingness to pay: individuals will have more willingness to pay for more severe status.

Some factors for avoiding medical care, reviewed by Taber et al. (2014), are included in this model: most of reasons concerned to *Low perceived need to seek medical care* are implicitly in needs calculation (equation 2) and some of the reasons related with *Traditional barriers to medical care* are included in expected cost (equation 3), like costs or insurance. Reasons related with *Unfavourable evaluations of seeking medical care* and *Personality traits* factors were not considered for the implementation of this model.

The model proposed in this section is also consistent with the description of the *Behavioral health care utilization model* described in Andersen (1995) and in Aday and Andersen (2003). Equation 3 models a patient's perceived need of medical care as a function of his health status and his perception about how his symptoms are evolving. Equation 3 emphasises how the need for care is combined with enabling resources, as income, to define a patient's willingness to request medical treatment, while equation 5 reinforces this notion by introducing additional variables that influence the capacity of a patient to receive medical attention. The variable *tolerance* included in equation 5 can be understood as a variable that captures additional disturbances that affect how patients decide to visit a medical provider that could be related to biases on how they evaluate their own health, or their personal beliefs about health and health providers.

Empirical studies as Pohlmeier and Ulrich (1995), Deb and Trivedi (2002) and Hjortsberg (2003) have found significant results regarding the effect that severity and income have on the probability by which an individual will search for medical attention. Both variables seem to have a positive effect on the increase this probability. Pohlmeier and Ulrich (1995) found a significant effect for chronic complaints and degree of disability, this is captured in our model by including severity on equation 2, since patients with a lower health status will be more sensible to any new illness that may affect their health. The effect of chronic diseases is also found in Deb and Trivedi (2002). Hjortsberg (2003) found that different types of costs involved in the acquisition of medical care have a significant reducing effect on the probability of visiting a doctor in Zambia, this is related to how increasing opportunity and travel costs has a disabling effect on the acquisition of medical care. In our model, this is captured by the inclusion of *transport costs* in equation 5.

3.3.4 Patient: follow up visits with a specialist

The decision to visit a doctor in the context of a referral from a GP to a specialist is considerably different. For our model, the decision on the first contact (see 3.3.2) of paramount importance. In contrast, we use a rather simple implementation for the follow up visits once the patient is in the system. We argue that whenever a patient can economically afford to go to the follow up visit, he or she does so.

3.3.5 Patient: death

Death is modelled similar to the original proposal by Grossman (1972) and occurs whenever the health status falls short of zero. Put differently, whenever the sum of severity of all medical conditions is above unity.

$$death_{it} = \mathbb{1}\left(1 < \sum_{m \in M_{it}} S_m\right) \tag{8}$$

where M_{it} is the vector of all medical conditions of individual i at time t and S_m is the severity of medical condition m. Note that in this case the visibility of symptoms is irrelevant.

3.3.6 Choice of health-care provider

Patients do not only have to decide whether to enter or not the health-care system, but also which provider to visit. We start from the idea that each patient has a family doctor (FD) which is normally a general practitioner (GP). Under normal circumstances, patients will enter the system through their FD and hence there is no choice. Nevertheless, there are three situation in which the patient actually has to choose the service provider:

1. At the beginning, the patient might not yet have a FD and therefore has to choose one.
2. If the patient is not satisfied with the current FD, a new one might be chosen.
3. In case of a referral to a specialist, the patient might need to choose among several options.

The choice of the provider depends mainly on two elements: trust[1] in the provider's ability and the expected cost.

[1] We understand as trust the level of confidence in the ability of the provider. This level of confidence will be endogenously generated through experiences of the patient and members of his/her social network.

- **Personal trust in providers**: trust in the provider is key in the patient-provider relationship. We model trust as result of good experiences (correct diagnosis) in the past. For the evaluation of providers where the patients was never attended, the patient uses the evaluation of members of his/her social network to estimate the quality of the provider.
- **Expected costs**: The choice of provider will also depend on the expected out-of-pocket cost. In addition to the medical cost, we also consider transportation cost and opportunity costs[2].

We can formalise this choice using the following decision:

$$p^* = \underset{p}{\operatorname{argmax}}\ e(trust_{ip}, E[cost_{ip}]) \tag{9}$$

where $e(.)$ is an evaluation function of providers with[3] $\partial_1 e > 0$ and $\partial_2 e < 0$, $trust_{ip}$ is the level of trust of individual i in provider p and $E[cost_{ip}]$ is the expected OOP expenditures of individual i when going to provider p. We will now discuss each of the two arguments individually.

Trust in provider

Regarding personal and network trust in a provider, we define them as follows:

$$trust_{ip} = \begin{cases} \frac{n^s_{ip} - \eta \cdot (n_{ip} - n^s_{ip})}{\sqrt{n_{ip}}} & \text{if } n_{ip} > 0 \\ \frac{1}{\sum_{j \in SN_i} w_j} \sum_{j \in SN_i} w_j \cdot trust_{jp} & if n_{ip} = 0 \end{cases} \tag{10}$$

where n^s_{ip} number of contacts between individual i and provider p with a successful outcome (e.g. correct diagnosis) out of all contacts between the two denoted n_{ip}. The parameter η captures how much more a negative experience is valued as compared to a positive experience. We assume that $\eta \geq 1$ because patients typically weight a bad experience more than a good experience [REFERENCES]. SN_i is the social network of individual i, is comprised of the individuals closest to the patient in the grid. If an individual i has no personal experience with provider p, individual i can use the weighted average trust of people in his or her social network. The weight factor w_{ij} can allow us to give more weight to the opinion of people closer in the social network, though in the first version of the model this weight is equal to 1 for all members of the social network.

Expected out-of-pocket expenditures

The expected out-of-pocket expenditure is second argument for the evaluation of providers according to equation (9). We use the following implementation:

$$E[cost_{ip}] = transportCost_{ip} + consultCost(h, i, p) + \pi_p Y_i \tag{11}$$

[2] Opportunity costs can include the time required to get attended or some type of administrative burden

[3] We use this short notation $\partial_1 e$ to denote the first derivative of function e(.) with respect to the first argument: $\partial_1 e \equiv \frac{\partial e(x,y)}{\partial x}$

where $transportCost_{ip}$ refers to the transportation cost for individual i when visiting provider p, which is simply $distance \times pricePerDistance$. The second term refers to the expected out-of-pocket expenditures of the visit which is a function of the provider p, individual i (e.g. medical condition) and the health insurance plan h. Finally, the last term $\pi_p Y_i$ captures a possible opportunity cost which is increasing with the income of the individual. As example, we might think of long waiting times at public hospitals during which the person cannot work. In our setting, the parameter π_p captures the global amount of such opportunity costs, which is a characteristic of the provider.

3.4 Submodel: providers

3.4.1 Objective function of providers

Before discussing detailed decisions made by the providers, let us discuss the general goal of providers. We assume that providers care about two key elements:

1. Well-being of patients
2. Their own economic success

First and foremost providers are interested in helping patients to recover from medical conditions. Hence, the health status of the patients directly enters the objective function of providers. Besides this rather altruistic objective, providers also have to make sure their business is economically viable. Hence, their benefit also enters the objective function. The economic success will depend on the number of patients, which itself is expected to depend on the quality of service the provider offers.

Let us define the objective function O_p as follows, assuming a simple Cobb-Douglas function (to be discussed!):

$$O_p(MS_p, \Pi_p) = {MS_p}^{\alpha} \times {\Pi_p}^{1-\alpha} \tag{12}$$

where MS_p is the medical success of provider p and Π_p is the economic benefit of provider p. The weighting α of each of the elements can be defined at the provider level. For values of α close to unity the provider would only care about the medical success, while values close o zero would put the emphasise on the economic success. We draw alpha from a Uniform distribution bounded at 0.4 and 0.6. The medical success MS_p is defined by the proportion of correctly diagnosed medical conditions.

3.4.2 Provider.appointment

The decision to seek medical assistance relies on the patient (see 3.3.2), but once the patient decided to visit a health care provider, the provider is mainly in charge of the outcome. We implement the medical consultation as follows:

1. The provider decides how much to invest in diagnostics (see 3.4.3) based on this general appreciation of the patient (proxied by the actual health status) and his/her base level of diagnostics (which can depend on investment and the objective function).
2. Based on the investment in diagnostics, the provider is able to detect each of the medical conditions with a certain probability. The probability of a correct diagnosis (see 3.4.4) depends on various factors such as the general difficulty of detection, the ability of health care provider and the investment in diagnostics.
3. If the provider reaches a diagnosis (correct or not), there are two possibilities:
   (a) The provider has a treatment (e.g. GPs might not have access to all treatments) and prescribes this treatment. Here we model the process of treatment selection (see 3.4.5) based on knowledge but also economic interests.

(b) The provider is unable to prescribe a treatment and refers the patient to a specialist.

3.4.3 Decision on investment in diagnostics

Diagnosing a medical condition is not an easy task, especially because there are many unknown elements. Using a series of diagnostics therefore helps identifying the correct diagnosis. The key challenge here is that the decision on how much diagnostics is required must be made beforehand. Let us assume that the following factors affect the amount of diagnostics:

Effects of amount of diagnostics:

Factor	Effect	Reasoning
General health status of patient	Positive	If a patient has a more severe general health status the provider might choose to carry out more diagnostics because (1) it might be more urgent and (2) the likelihood of a severe illness which is hard to detect might be larger.
Marginal benefit for provider	Positive	Some diagnostics might be economically more interesting than others. Hence, if the doctor can earn more on each diagnostics, he/she might be more likely to use them.
Cost of diagnostics	Negative	The cost of diagnostics might negatively affect its use. This is because the provider might actually care about the cost of the intervention.

In order to avoid having to make strong assumptions on how medical providers actually decide, we use directional learning (Proportional Integrative Derivative (PID) controllers (see 3.7.1) based on the objective function of provider. The idea is be to have a set of parameters according to which the level of diagnostics is defined and then use a directional learning algorithm to find the best values for each doctor.

Let us assume the following functional form:

$$D_{pi} = \delta_0 + \delta_1(1 - HS_i) \tag{13}$$

where δ_0 would be the standard amount of diagnostics ($\delta_0 \geq 0$) and δ_1 would capture the marginal increment in diagnostics due to the severity of the medical conditions.

3.4.4 Probability of correct diagnosis

In our simplified model we assume four factors to play a role when it comes to the likelihood of a correct diagnosis.

Factor	Effect
Ability of the provider	Positive
Difficulty of detection of illness	Negative
Investment in diagnostics	Positive, but depending on illness
Number of simultaneous medical conditions	Negative

We define the probability of a correct diagnosis $P(CD|mc = m)$ for the medical condition m as:

$$P(CD|mc = m) = \frac{A_p}{{M_p}^{\alpha_m}} \left[\pi_m^0 + \min(\pi_m^0 \times D_{pi}, \pi_{m^{max}})\right] \quad (14)$$

where $A_p \in (0, 1)$ is the ability of the provider, M_p the number of simultaneous medical conditions, and π_m^0, π_m^0 and π_m^{max} are illness specific probabilities of detection and sensitivity to the investment in diagnostics. The parameter α_m captures the sensibility of the probability to the number of simultaneous medical conditions.

3.4.5 Treatment selection

Let T_m be the set of possible treatments for the medical condition m. The provider therefore selects t^* such that it maximises his/her evaluation function $s(t)$.

$$t^*_{mi} = \text{argmax}_t \ s(t) \ \ \forall \ t \in \ T_m \quad (15)$$

Hence, all the decision making process regarding the best treatment will depend on the way $s(.)$ is defined. Given that this decision is a crucial one for the whole model and that many implementations are possible, we opt for a very general and parametrised version. The following table displays the factors that are likely to influence in the decision:

Factor	Effect
Effectiveness of treatment	Positive
Efficiency of treatment (effectiveness/cost)	Positive
Cost	Weakly negative
Marginal benefit for provider	Weakly positive
Side effects	Negative (not modelled yet)

Our implementation is carried out in two steps:

1. Treatments are evaluated by their cost and their effectiveness. Only a limited number of treatments are then selected. The relative importance of cost vs. effectiveness is parametrised.
2. The provider then selected among the eligible treatments the one which provides him/her the most benefit[4].

[4] In the first step we have a parameter allowing to turn off completely the importance of the marginal benefit to the provider

More specifically, the implementation is implemented as follows. First we define a score function which considers both the total cost and the expected duration of treatment. The goal is to minimise this function.

$$s(t) = cost_t + \gamma_E \frac{S_m}{\Delta S_m(t)} \tag{16}$$

Let us now define $s^*(t) = \min s(t) \; \forall \; t \in T$ as being the treatment that would minimise the function. Rather than taking directly this best treatment, we continue to consider all treatments which are not too distant to the best.

$$T^* = \{t : \; T_{mc} \mid s(t) \leq \delta s^*(t)\} \tag{17}$$

where $\delta \geq 1$. Among this smaller list of treatments, the provider selects the one with the highest marginal benefit for himself.

$$t^* = \max_t MB_p(t) \forall t \in T^* \tag{18}$$

Hence, the full selection process of the treatment is governed by only two parameters. *gamma* captures the relative importance of effectiveness over cost and δ manages the importance of the marginal benefit to the provider. Both parameters can be defined at the model level (simple version) and are therefore the same and constant for all or at the individual level, where providers would learn to find the best value over time through our PID controller (see 3.7.1).

3.5 Submodel: health insurance plans

There are many health insurance plans available in the different countries, some with very country-specific characteristics. Our models aims at being flexible and therefore each health insurance plan (HIP) is characterised by a series of parameters. The following table highlights the key parameters of each HIP:

Parameter	Explanation
insurer	Issuing insurance company
premium	Monthly premium to be paid by each insuree. For simplicity of the model, agents pay the corresponding amount in each week.
minAge	Minimum age for which the HIP is available (company policy)
maxAge	Maximum age up to which the HIP is available (company policy)
women	Women accepted as insurees
men	Men accepted as insurees
deductible	Deductible: claims until this amount have a 100% co-payment rate (⇒ zero reimbursement)
copaymentRate	Co-payment rate once the year-to-date claims reached the deductible and before reaching the stop-loss or stop-claim value
stopLoss	Amount after which the patient has no more cost-sharing[5] payment. For instance, if the deductible is 500 and the stopLoss is at 800, then the patient will pay a maximum of 300 in co-payment. stopClaim and stopLoss are mutually exclusive.
stopClaim	The stop-claim is the opposite of the stop-loss. Once the insurance company paid this amount of reimbursement, no more payments are accepted. stopClaim and stopLoss are mutually exclusive.
claimsYTD	Total amount of year-to-date claims. This is reset once a year
reimbursementYTD	Reimbursement to the patient since the beginning of the year

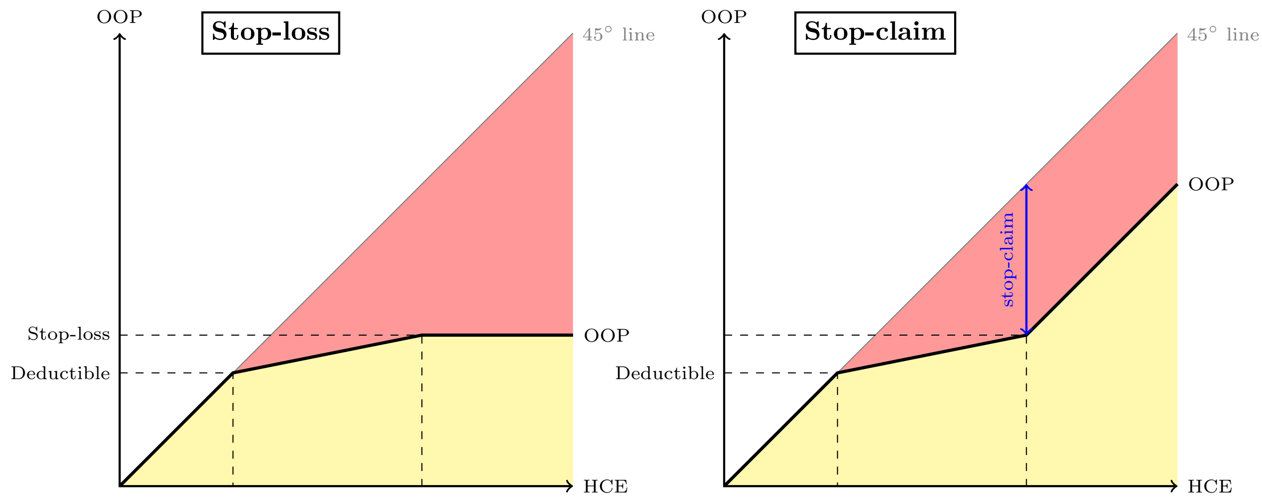
The key parameters here are **deductible**, **copaymentRate**, **stopLoss/stopClaim** as they can replicate a large number of possible settings. Let us first make the distinction (mutually exclusive) between an insurance with **stop-loss** and one with **stop-claim**. Figure 1 depicts the two main types of health-insurance-plans schematically.

On the left we have a plan with an initial deductible up to which all the HCE are covered by the patient. Once the deductible is reached, the patient continues to pay the co-payment-rate, which is generally very low (e.g. 5% or 10%). Once the total amount of out-of-pocket expenditures (deductible + co-payement) reach the level of stop-loss, the co-payment rate becomes 0% and the health insurance covers all the expenditures.

In the case of a stop-claim insurance plan the start is similar, but once the insurance company paid the amount equivalent to the stop-claim parameter, it no longer reimburses the patient. Hence, the co-payment rate goes back to 100%.

Of course, by changing the parameters, we can also include simpler health-insurance plans, such as the examples displayed in the following table:

Figure 1: Schematic representation of the two core types of HIP



D	CP	SL	SC	Explanation
0	0	0	–	Full coverage of all costs at any level of claim (e.g. free public health care)
500	–	500	–	Insurance with no co-payment element: only deductible, then 100% reimbursement
0	5%	∞	–	Insurance with no deductible and no stop-loss
500	–	–	50'000	Insurance with no co-payment element: only deductible, then 100% reimbursement up to a maximum of 50'000. For higher expenditure there is no more coverage

D: deductible, **CP**: co-payment rate, **SL**: stop-loss, **SC**: stop-claim

3.6 Submodel: insurance companies

3.6.1 Updating Health Insurance premiums

Every 52 periods, each Insurance Company updates the premiums that must be paid for each of its Health Insurance Plans. When the parameter set does not allow insurance companies to make profits, we use a rather simple approach. Companies determine the HIPs premiums for the next 52-period simply by computing the mean reimbursement for each of their Health Insurance Plans, following the next set of equations:

$$p_{s_j,t} = \frac{r_{s_j,t-1}}{|a_{s_j,t-1}|} \qquad \forall s_j \in S_j \tag{19}$$

where:

- $s_j \in S_j$ is a Health Insurance Plan offered by Insurance Company j.
- S_j is the set of all the Health Insurance Plans offered by j.
- $p_{s_j,t}$ is the premium that must be paid for s_j in t.
- $r_{s_j,t}$ is the total amount of reimbursements associated to s_j during t.
- $a_{s_j,t}$ is the set of Patients that hired s_j in t.
- t is a 52-tick period.

Note that for the stability of the model we also introduced two parameters to limit the annual changes in the premiums.

When insurance companies are allowed to make profit, the model changes to the use of a PID Controller, which computes a new premium from the last two periods' profits and premiums. This computation is performed a number of times equal to the number of HI Plans offered by j, according to the following equation (Proportional Integrative Derivative (PID) controllers (see 3.7.1)):

$$p_{s_j,t} = \min\{p_{s_j,t-1} + \alpha\frac{\Delta\Pi_{s_j,t-1}}{\Delta p_{s_j,t-1}}, \quad p_{s_j,t-1}(1+\beta)\} \tag{20}$$

where

- s_j is a Health Insurance Plan offered by Insurance Company j.
- p_{s_j} is the premium that must be paid for s_j.
- Π_{s_j} are Insurance Company j's profits associated to s_j.
- α is the PID Controller's sensibility parameter.
- β is the maximum allowed raise rate for premiums between periods, and is determined exogenously by a regulatory entity (when applicable).
- t is a one-year period.

On the other hand, an Insurance Company computes its profits associated to Health Insurance s_j in time t as follows:

$$\Pi_{s_j,t} = \sum_{i\in a_{s_j,t}} (p_{s_j,t} - loss_{i,t}) \tag{21}$$

where

- a_{s_j} is the set of Patients that hired s_j.
- p_{s_j} is the premium a Patient must pay for s_j.
- $loss_i$ is the amount reimbursed to Patient i by j during a given one-year period.
- t is a one-year period.

3.7 Submodel: other submodels

3.7.1 PID controller

For several decisions in our model we are able to define a objective function but implementing the whole decision making process behind this function would be beyond the reach of this version of the model. We therefore use a simplified and adapted version of the PID controller for discrete time models proposed by Carrella (2014). The idea of the PID controller can be paraphrased by a *trial-and-error* approach where the agent changes her parameters and looks whether the objective function moves in the correct direction. In general, we can define the PID controller as follows:

$$\delta_{it} = \delta_{i,t-1} + \alpha_P\frac{\Delta P_{i,t-1}}{\Delta\delta_{i,t-1}} \tag{22}$$

where δ_{it} is the parameter of interest of individual i in time period t and P_{it} is the objective function. *alpha* is a simple parameter of the PID controller handling the sensitivity of the behaviour to changes in the objective function. For our model the use of PID rather than a fixed behaviour has the important advantage of being able to handle policy changes that might affect the whole decision making behaviour.

4 Additional material

4.1 Overview of indices, symbols and parameters

Table 3: Overview of indices and symbols

Index	Description
i	Individuals/patients
p	Providers
c	Insurance companies
m	Medical conditions
h	Health insurance plan
t	Time dimension (measured in weeks)
Symbol	**Description**
S_m	Severity of medical condition m
d_m	Duration of visible symptoms of medical condition m

4.2 List of parameters and variables used in the model

In this section we summarise the exogenous parameters used in the model.

Param.	Description	Eq.	Value
M	Number of weeks in the past that the patient considers when estimating own health expenditures	1	260
ω_i	Relative weight given to catastrophic events in subjective estimation of the Patient's own health expenditures; random draw from a $Beta(\alpha, \beta)$ distribution	1	$\alpha = 5$ $\beta = 1.5$
γ	Scaling factor of willingness to pay function	4	150
α	Relative importance of medical needs net tolerance in willingness to pay function	4	1.5
β	Relative importance of income in willingness to pay function	4	0.95
t_i	Patient's tolerance to medical needs	4	0.0
η	Relative weight of negative experiences with a Provider vs. positive ones in determining a Patient's trust	10	1.5
$w_{i,j}$	Relative weight (importance) given to the opinion of people close to the individual i in the social network	10	1
$pricePerDistance$	Cost per unit of distance of transportation from Patient's location to Provider	11	0.01
π_p	Amount of non-monetary costs associated with Provider p	11	0.0
Y_i	Income of Patient i, drawn from a log-Normal distribution	11	$\mu = 3.62$ $\sigma = 0.469$
α	Relative importance (exponent) given to medical success vs. economic profit in Provider's objective function.	12	$\alpha \sim U[0.4, 0.6]$
A_p	Provider ability in diagnostics	14	$A_p \sim U[0.8, 1]$
α_m	Difficulty of detection of Illness m	14	0.8
γ_E	Weight given to effectiveness in score function for Treatments	16	1.5
ζ	Cost associated to changing to another HIPlan different than the one hired last year		$\sim U[1, 1, 3]$
δ_{s*}	Range of scores above the minimum that the Provider considers when selecting Treatments	17	1.5
α_P	PID controller parameter handling the sensitivity to behaviour to changes in the objective function	22	2
$\alpha_{P'}$	Sensitivity of the PID that controls the changes in premiums to changes	Model params	0.5
$interestDebt$	Intrest rate applied to debt		0.05
$solvencyRequirement$	Proportion of risk that insurance companies don't need to cover; based on legal context	Model params	0.05

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