How to Build an Agent-based Model to Assess the Impact of Co-payment for Health Services

Angela Testi, Michele Sonnessa and Elena Tànfani
Department of Economics, University of Genova, Via Vivaldi 5, Genova, Italy

Keywords: Agent-based Models, Economic Simulation, Health Care Financing.

Abstract: Some forms of co-payment are required in insurance markets to avoid moral hazard that in health sector entails excessive consumption and costs. Literature and empirical findings, however, do not agree about the effectiveness of co-payment in practical situations. Moreover, in health systems co-payment seems to be more aimed to help in financing than to reduce moral hazard. The final impact of co-payment is rather difficult to predict due to these conflicting aims. Assessing the impact of a co-payment policy is, however, very important, because it affects also the principles of universalistic health systems threatening equity attainment. The specific aim of this paper is to propose an Agent-based simulation model that allows both i) to take into account all these contradictory effects at the same time, ii) to compare different co-payment models. The model development is presented mixing empirical data with some stochastic assumptions the authors intend to test.

1 INTRODUCTION

Insurance companies use co-payments to share health care costs and prevent moral hazard, that is post contractual opportunistic behavior to transfer more risks to insurance company. In absence of some co-sharing tools, this behavior leads to inefficient situations, excessive consumption and higher costs. Though co-payment is often a small portion of the actual cost of the medical service, it is meant to prevent people from seeking medical care that may not be necessary. The underlying philosophy is that with no co-payment, people will consume much more health care services than they otherwise would if they were paying for all or some of them. Co-payment may, however, be ineffective in presence of relevant Supply-Induced-Demand effect, i.e. when services are not demanded directly by the patient, but by the physician, acting as patient "agent". In this case excessive consumption, due to moral hazard, will not be reduced and even we could predict a further increase (Ellis and McGuire, 1993). However, also in case of moral hazard reduction, the crucial issue is that co-payment should reduce only not essential consumption, without discouraging people from seeking necessary medical care. This can be done, applying co-sharing measures (e.g. tickets or ceiling, or caps) on more elastic consumption items.

The above described mechanism is, however, based only on a theoretical model. From an empirical point of view, co-payment acts as a rationing device preventing access to care in universalistic systems as literature shows (Louckx, 2002). And even if no definite result is given, many empirical papers, from the more complete and cited (Manning et al, 1988), predict effects of consumption restriction of the more frail and deprived people, engendering negative effects on their health status. It seems that co-payment gives rise to the classical trade-off between equity and efficiency, where the only demonstrated effects are the negative ones on equity, because gains in terms of efficiency and cost containment are not clearly verified by empirical literature (Carrieri, 2010).

What makes things more difficult is, however, that in practical application, co-payment is not utilized, as theory prescribes, to reduce moral hazard, but almost exclusively as a tax to finance public budget. This is, however, a practical aim opposite to the theoretical one, entailing that to be more effective, co-payment should not change consumption, which is exactly the opposite of co-payment intended to reduce moral hazard.

If co-payment should improve public balance, it should be imposed on the "less" elastic items, not to

Testi A., Sonnessa M. and Tànfani E..
How to Build an Agent-based Model to Assess the Impact of Co-payment for Health Services.
DOI: 10.5220/0004166205560563
In *Proceedings of the 2nd International Conference on Simulation and Modeling Methodologies, Technologies and Applications* (HA-2012), pages 556-563
ISBN: 978-989-8565-20-4

the "more" elastic ones: this means on the more essential services, the ones that patient do not reduce even if their price increases. In this case negative effects on equity are still larger, because being a form of financing not linked to the ability to pay, but rather to the use of services, it requires greater contribution from the least well-off (Wagstaff et al., 1999), even if to attenuate partially this undesirable effect some exemption rules are usually implemented.

As far as we know the impact on the public budget of the introduction of a co-payment system has never been studied in detail, nor who bears the greatest disadvantage. We can predict that as co-payment is perceived as a price by the patient, a price increase means reducing demand, but how much demand reduces depends on elasticity. Following traditional microeconomics, we know that elasticity depends on price effect, which, in its turn is composed by a *substitution* and an *income* effect. The first effect depends on how many substitutes exist, while the income effect on how large the income is in absolute term and how large health expenses are in relative term with respect to other goods. If the aim is to finance health services, co-payment should be applied to services with a rigid demand, that is were no substitution effect exists and health expenses are high during a year, for instance in chronic conditions. This is, of course, contraindicated for equity, so, before recurring to co-payment in universalistic systems, decision makers should know in advance: i) whether increasing co-payment will make people reduce their demand for services and / or getting no consistent fiscal return and ii) what is the best exemption structure to correct excessive payment from chronic or deprived patients.

In particular, since 2000, the Italian experience, developed in some different ways following the regional policies, includes diverse experiences of co-payment on drugs, diagnostic and specialist visits, differently designed in the Italian regions. From a point of view aggregate and almost exclusively for drugs there are some data showing what has been the impact (http://www.agenziafarmaco.gov.it/it/content /osservatorio-sull%E2%80%99impiego-dei-medici nali-osmed). Data on specialist visits, diagnostic and revenue that has been obtained during the years are, however, missing, even if some preliminary information were given during a national Conference in Rome, last May (http://www.agenas.it/agenas_pdf/Dossier%20Co-payment_aprile2012.pdf). The same happens for the effects on different categories of exempt people. In this research still in course, it appeared that, generally, the patients who cannot profit by exemption consume less medicines, diagnostic and specialist visits than the exempted ones. From this strong, and not yet published evidence of under treatment, the empirical aspect of this study took start.

In this paper, we propose an Agent-based modeling framework aimed at investigating the effects of different co-payment rules.This model can represent a useful support to decision makers, increasing the capacity to control the adverse consequence of co-payment on equity of access.

The reminder of the paper is as follows. In Section 2 an agent-based simulation model is described intended to be a tool for better decision making about definition of more effective co-payment policy. Section 3 provides an overview of the LigurNet database the model is built upon. Section 4 indicates conclusion and further work.

2 AGENT-BASED MODEL

In economic research increasing attention is given to agents' characteristics and their interaction to determine aggregate results. This is crucial in complex situation as co-payment is. Since it is impossible to verify single economic theory, agent based models seem to be preferable because they can predict the results of conflicting aims and behaviors. Aggregate levels of the main decision variables, such as total expenditure, co-payment returns, consumption, and so on, are derived starting from the individual behaviors.

In fact, as stated in Ostrom (1988), and to some extent in Gilbert and Terna (2000), computer simulation can combine the extreme flexibility of a computer code where we can create agents who act, make choices, and react to the choices of other agents and to the modifications of their environment and its intrinsic computability.

Economic policy advice requires a thorough understanding of the relevant individual choices that are responsible for the effects of policy measures in the economy, as well as in the public health system.

Theoretical work based on certain model structures accompanied by empirical evidence aims at giving us guidance on the causal relationship of key economic variables.

Agent-based models can improve the possibilities of a modeler to capture economic phenomena that seem relevant to policy makers and extend the set of questions that can be asked about policy effects.

The choice of agent based paradigm for studying the co-payment system is mainly due to two reasons: its algorithmic flexibility and the need for a multilevel interaction.

The rules to value the co-payment of each prescription are based on algorithms and legislators often change them deeply. So in order to effectively adapt the model to different co-payment scenarios, we opted out for the agent based modeling technique. Moreover, we are interested in understanding how interaction phenomena can affect the individual choices, in terms of selection of public or private health provider by citizens. As also stated in Howitt et al. (2008), an agent-based model is a way to create virtual worlds that can be used as test beds to study macroeconomic phenomena, considering interactions among agents simultaneously with agent decisions.

2.1 General Structure of the Model

The Agent-based modeling is a strongly micro-founded approach to study economic dynamics. It is interested in detecting the patterns at aggregated levels of analysis that origin from the interaction of agents, who follow particular behavioral rules and may be constrained in their choices by various institutional arrangements.

Nevertheless, the aggregate behavior of the system can be well depicted in terms of cause-effect structure, where the final result depends on agents characteristics, their incentive design mechanism and co-payment structure.

The agent-based model introduced in present work is aimed at modeling individual behavior and interactions among three classes of agents (patients, physicians and public decision-makers). The general macro structure of the model can be described by the cause-effect diagram in Figure 1.

The model controls three relevant variables: public budget, prescription level and co-payment level.

Public Budget depends on prescription level and is defined by two tools: "moral suasion" exerted by Health Authorities on physicians" and "co-payment level". It represents the key driver in the policy maker decision function.

Prescription Level depends on the behavior of two agent types: the physician (propensity to prescribe) and the patient rate of demand for prescription. The level of prescription determines both the public budget level as well as the patient utility.

Co-payment Level depends on the policy maker decision, taking into account public budget as budgetary constraint and the patient utility, as directly connected with public consensus. Given the health status of the patient, the co-payment level determines the propensity to demand health services; the difference between what the patient expects on the basis on his health status and what the doctor prescribes determines the patient utility.

The patient utility depends on the number of prescriptions requested (the so called "expressed demand"), following their perceived "want", and on the number of prescriptions really delivered by physicians, following what they think is the patient's "need" (Culyer and Wagstaff, 1993).

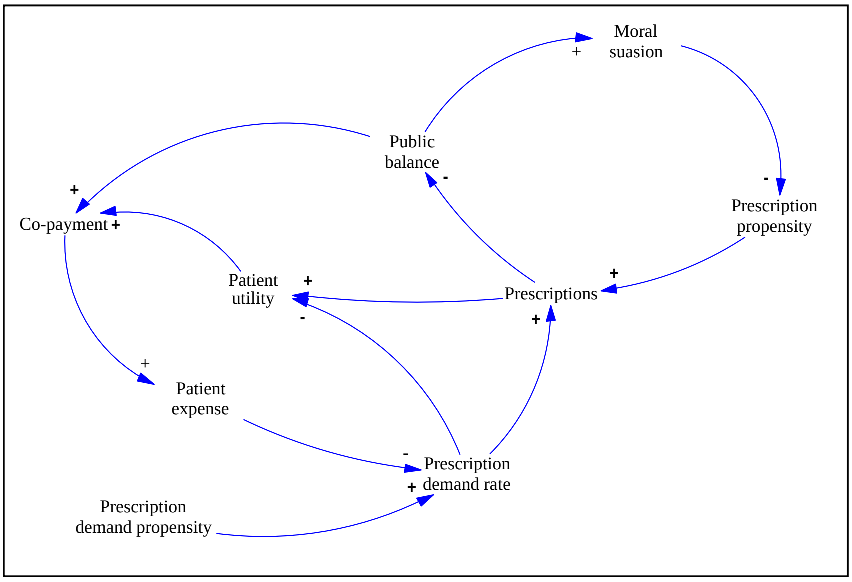

Figure 1: Cause-effect diagram.

2.2 Model Implementation

The model is closely linked to a large empirical dataset (see Section 3), so it has been implemented in native Java language using JAS libraries (described at http://jaslibrary.sourceforge.net). This choice grants an efficient interaction with the database, containing the population and the prescriptions of the last ten years. In fact, as stated in Boero and Squazzoni (2005), "*...attention has been paid to the need of integrating ABMs (and simulation models generally speaking) and methods to infer data from empirical reality, such as qualitative, quantitative, experimental and participatory methods [...]. The link between empirical data, model construction and validation needs to be thought and practised as a circular process for which the overall goal is not merely to get a validation of simulation results, but to empirically test theoretical mechanisms behind the model. Empirical data are needed both to build sound micro specifications of the model and to validate macro results of simulation. Models should be both empirically calibrated and empirically validated. This is the reason why we often enlarge our analysis to the broader quest of the use of empirical data in ABMs, with respect to the narrow quest of the empirical validation*".

The approach we follow in implementing the model consists in utilizing both current empirical data and integrating them with strong hypothesis for variables that cannot be directly observed from available data.

According to the methodology proposed in Richiardi et al. (2006), the general structure of classes, entities and schedule is represented in terms of class diagram (Figure 2) to represent the agent characteristics as well as the information/documents they create and exchange and in terms of time-sequence diagram to describe when things happen within a simulation experiment (see Section 2.3).

Taking into account the general structure of the model, three classes of agents are introduced. The characteristics and properties of each agent class are described in the next subsections. The model also defines the list of the patient's pathologies with corresponding exemptions if any and a collection of *PrescriptionRequests*, *i.e.* objects that trace the lifecycle of a single prescription request, to collect aggregate variables such as patients' utility, patient expense and general regional expenditure.

The prescription request object is characterized by the following properties:

- Prescription type (Medicine, Specialist Visits, Exams and controls);
- Final price for National Health Service;
- Price for patient (taking into account co-payment amount);
- Prescribed (boolean value).

Moreover, the following general parameters are defined:

- Number of patients;
- Number of physicians;
- Co-payment level and design (e.g. fixed amount, percentage of the price of the service,

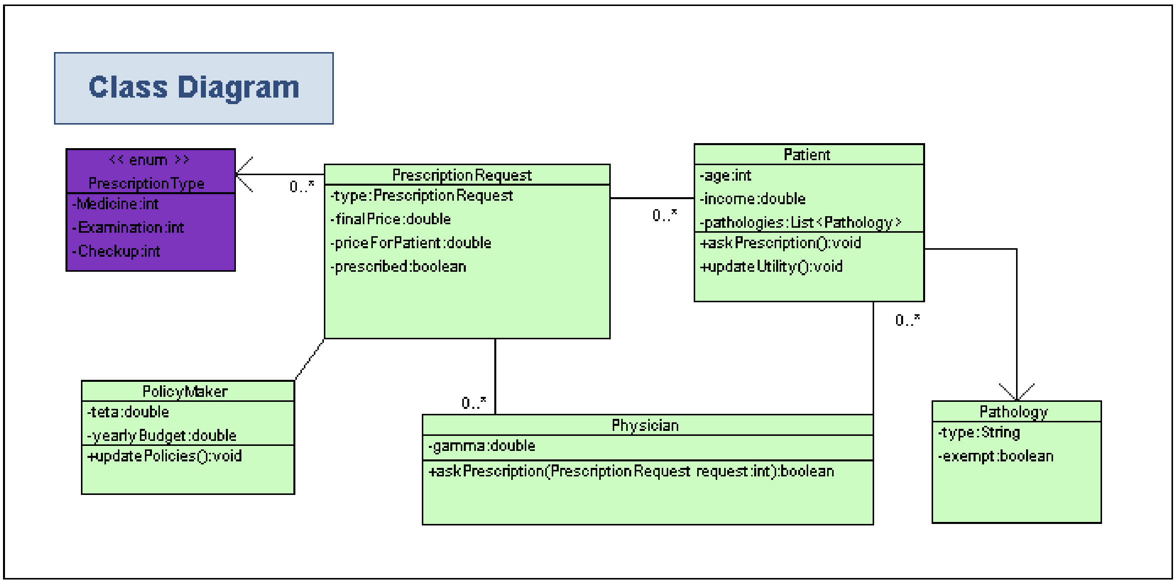

Figure 2: Class diagram of the model.

ceiling, etc.)

- Income distribution of patients.
- λ: it is a parameter of the patient: it defines the share of health spending relative to income, which represents utility of 0. In other words, it is the sum of what has been paid within a year compared to one's income that is considered acceptable. This coefficient is assumed to be equal for all patients.
- γ_m is a parameter of the physician. It represents the tendency to meet patient demand for prescription.

2.2.1 Patient Agent Class

Every patient agent is characterized by following own properties:

- Age [E];
- Income [R];
- Pathologies [M];
- Exemptions [Me];

We assume that agents require prescriptions depending on their health status (i.e. the number of pathologies directly influences the number of required prescriptions) and their level of income. The individual demand function, for a given class of patient age and health status, has the form shown in Figure 3.

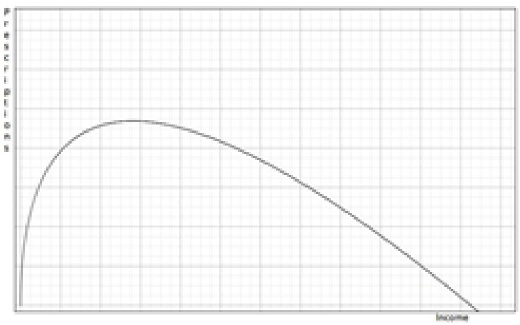

Figure 3 Individual demand function.

For different combinations of ages and number of pathologies we can define different demand functions and test their correspondence in empirical data.

The demand for prescription depends on: i) the health status (proxied by the number of pathologies) which is introduced into the model using empirical data and can change over simulation time; ii) the yearly income.

The particular form of the demand curve depends on the trade-off between the two components: the level of pathologies increases the prescription demand, while the level of income decreases it, since rich people are supposed to use more private health services than poor ones. The position of the demand curve depends on the individual exemption regime: different exemption facilities may have different impact on the individual income and, therefore, at parity of total income increase or decrease the number of required prescription (shift the curve upwards or downwards), given the same health status.

Every simulated year, agents compute their own utility level, depending, negatively, on the expenditure and, positively, on the prescriptions received by the physician. More in detail, the utility level for patient i at time t is computed by the following equation:

$$U_t^i = \lambda - \frac{X_t^i}{\Pi^i} + \frac{\sum op - \sum rq}{\sum rp} \tag{1}$$

Note that, the utility is made up of two components:

- the difference between λ (percentage of health expenditure, giving a null level of utility) and the individual expenditure quota for health services, computed as the ratio between $X_t^i = \sum P_j$, where P_j is the price paid for prescription j by patient I, and the total income Π^i of patient i;
- the percentage difference between the obtained prescriptions (*op*). and the requested ones (*rp*).

The price P_j is intended as the final price for patient, including the effect of co-payment and exemptions. We assume that, the percentage λ does not depend on the individual level of income. Moreover, it possible to relax this assumption and modeling the relationship between the parameter λ and the individual income. On the contrary, patient behaviour evolves over simulation time, since its status in terms of pathologies and exemptions can change over time.

The agent population is built from empirical data collected in the GP LigurNet database (see next section for detailed description). The data set provides identities of agents, with the list of pathologies and exemptions they obtained in the past. Unfortunately, the income level is not available in database, so it is randomly assigned by the simulation model based on a normal distribution according official data of ISTAT Multiscopo Survey (www.istat.it) and Banca Italia Survey on Income of the Italian families (www.bancaditalia.it/statistiche /ibf).

At each simulation step, the agent decides if a new prescription should be asked to its physician. This choice is mainly driven by the empirical dataset. The prescription request is communicated to the patient's physician and internal accounting is modified according to its response.

2.2.2 Physician Agent Class

Physician is characterized by the tendency to go along with patient demands [γ_m]. The agent is able to react to patients' prescription requests. For each request, the physician has to decide if to prescribe it or not.

Prescription rate depends on physician individual tendency to go along with patient requests, affected by general level of moral suasion coming from the policy maker. For each prescription request a uniform random sample is generated in the range [0,1]. If the sample is greater than the threshold level, computed as $\gamma_{m*}\theta$, the prescription is granted.

The γ_m parameter is introduced according the principle of "defensive medicine" leading to "supply-induced demand": the physician generally tends to give into patients requests, to avoid legal risks. This phenomenon is modified by moral suasion level θ applied by legislator. We assume that physician behaviour does not evolve over simulation time. The individual values of the γ_m parameter are randomly generated from a normal distribution.

Physician agents react to external stimuli. In particular, they are waiting for patients' requests and decide if according them or not. This implementations reflects real physician strategy. In fact they respond to the so called "waiting medicine" criteria. They are not supposed to be active in contacting patients and stimulating care.

2.2.3 Policy Maker Agent Class

The policy maker represents a single agent instance able to influence the whole system with its actions. It modifies its choices observing aggregate endogenous variables deriving from other agents' behaviour, in particular by the patients' utility.

Policy maker is characterized by own following properties:

- yearly budget [B];
- moral suasion level [θ].

In the first version no evolutive behaviour are provided. This means that Policy maker does not change its parameters during each simulation run. Different parameter combinations are tested comparing different simulation run outcomes.

Through the collection of system responses to changes in policy parameters, we can provide a sensitivity analysis of the key variables the policy maker can act upon, to reduce public expense and increase overall patients' utility.

It the first model configuration policy maker is characterized by a fixed behaviour which is initially determined as a simulation parameter. Future model improvements should take into account the possibility that policy maker's choices, in terms of moral suasion and co-payment, can change over

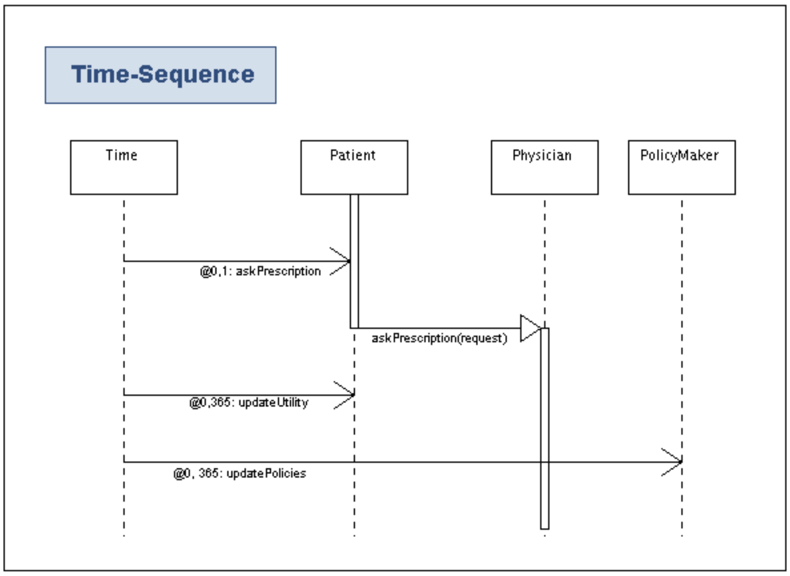

Figure 4: Time-sequence diagram of the model.

simulation time according to balance trends and aggregate patient utility.

2.3 Simulation Time Schedule

The dynamic of the model (Figure 4) is trivial. For each simulation step all patients decide whether to require a prescription, according the general probability and their own individual characteristics. In case a request is generated it is processed by the physician, who can approve it or not.

Every simulated year of simulation, the model updates the statistics and eventually asks the policy maker to guess changes in regulation.

3 DATA COLLECTION

As said above, the model is closely linked to a large empirical dataset available thanks to the collaboration of GP-LIGUR.net, the Primary care Observatory of Regione Liguria, collecting clinical and prescription data of 188,568 citizens, by 134 physicians for the period June 2000-June 2011.

In Italy to accede the second and third level of publicly delivered care, the prescriptions of family doctors, or General Practitioners (GP), are required. They record prescriptions by using the same software (www.Millewin.it). Even if the registration does not constitute compulsory information debt by GP, therefore, the database is a huge mine of information, that until now, have never been used by policy makers. Moreover, data are particularly valuable as it is possible to build the history of every patient, which is important for implementing our model.

The original database was corrected according to quality requirements following a set of indicators fixed with the help of the physicians. This meant reducing the number of doctors from 134 to 81 and the prescriptions from about 37 millions to about 12 millions.

3.1 Methodology of Data Extraction

Three groups of pathologies were taken into consideration.

- Oncological diseases - breast K, K prostate
- Chronic cardiovascular and metabolic diseases
- Depressive syndromes

The first two groups (oncologic and cardiovascular) may give right to exemptions from ticket payment in particular conditions of income and age, as specified in (Table 1), that are a mix of income, age, and pathology conditions. The third group, is a chronic pathology not recognized by exemption rules except for a tiny subgroup (psychosis).

Note that exemption conditions reported are the ones currently applied in Regione Liguria. Italian citizens, in fact, can benefit of different conditions depending on which Region they live (Il sole24oreSanità, 2012).

3.2 Database Role for the Model

The database allows to define a population of agents characterized by all those properties that are important for the construction of the agent-based simulation model. In particular, the propensity to demand prescription of patients, the exemption choices that reduce the expected return from co-payment, the prescription policy of the physician and so on.

From a first inspection of database, we can affirm that current situation is affected by a deep iniquity that should be corrected. There is strong evidence, for instance, of "foregone" care at the expenses of not exempted. The last have systematically less access to essential care. This is particularly serious for cancer patients, who require maximum adhesion to treatment and could, in the event of noncompliance, have an immediate and serious impact on their health. It is, however, serious also for chronic cardiovascular and metabolic

Table 1: The current situation of exemption in Regione Liguria.

	POOR: Family income <36.150 Euro	RICH: Family income >36.150 Euro
YOUNG: age <65	Co-payment is due on every prescription	Co-payment is due on every prescription
OLD: age > 65	No co-payment on every prescription	Co-payment is due on every prescription
ILL+YOUNG: Recognized chronic pathology and age < 65	No co-payment on every prescription	Co-payment is due only on drug. No co-payment on specialist and exams
ILL+OLD: Recognized chronic pathology and age > 65	No co-payment on every prescription	Co-payment is due on every prescription

diseases, even if as we expect that patient affected by the three prevalent chronic diseases (diabetes, hypertension and ischemic heart disease) are less adherent with respect to the first group as they may perceive their pathology less important than cancer.

In addition, with regards to this third group, the database proves large undertreatment, which indicates that probably most of them exit the public system, given that they not only cannot be exempted but also they are consumer of class C drug (that is not supplied free by NHS). We can imagine that a further utilization of the model could be assessing the impact on public budget of enlarging the list of the recognized chronic pathologies. At present, there are, due to population aging, other pathologies that could be included, such as, for instance, depression, arthritis, venous insufficiency.

4 CONCLUSIONS AND FUTURE WORK

In this paper we argue that agent-based modelling applied to policy making in the public health system needs a methodological protocol allowing to mix empirical data with theoretical assumptions about individual behaviour and preferences.

In this respect, we wish to introduce formalised approach to mix behaviour modeling, real data coming from regional health system and co-payment rule algorithms into an agent based model.

The approach is aimed at showing that feeding a model with empirical data can improve the awareness and guide policy makers towards better choices in terms of co-payment rules, as well as, connect the model more closely to the real world that it intends to simulate.

In further research, we plan to computationally develop the prototype and use the appropriate techniques to explore changes into the structure of the prototype, in order to find more deep theoretical insights and validate assumption about correlation between patient income and their behavior in terms of exemption and the possibility they look at private health system.

Throughout an appropriate validation of individual behaviour, more reliable assuptions about the right co-payment system can be provided.

ACKNOWLEDGEMENTS

We wish to thank GP Ligurnet and, in particular, Dr Pierclaudio Brasesco for collaboration in supplying data. All the authors participate and acknowledge support from the Italian Ministry of Education, University and Research (MIUR), under the grant n. RBFR08IKSB - FIRB PROJECT.

REFERENCES

Boero, R. and Squazzoni F. (2005). Does Empirical Embeddedness Matter? Methodological Issues on Agent-Based *Models for Analytical Social Science*. *Journal of Artificial Societies and Social Simulation*, 8(4). Retrieved from: http://jasss.soc.surrey.ac.uk/8/4/6.html.

Carrieri, V. (2010). The Effects of Cost-Sharing in Health Care: What Do We Know From Empirical Evidence?. *Economia Politica:Journal of Analytical and Institutional Economics*, 27(2), 351-374.

Culyer, A. J. and Wagstaff, A. (1993), Equity and equality in health and healthcare. *Journal of Health Economics*, 12(4), 431-457.

Ellis, R. P. and McGuire, T. G. (1993). Supply-Side and Demand-Side Cost Sharing in Health Care. *The Journal of Economic Perspectives*, 7(4), 135-151.

Gilbert, N. and Terna P. (2000). How to build and use agent-based models in social science. *Mind & Society*, 1(1), 57-72. http://www.agenas.it/agenas_pdf/Dossier%20Co-payment_aprile2012.pdf

Howitt, P., Kirman A., Leijonhufvud A., Mehrling P. and Colander D. (2008). Beyond DSGE Models: Toward an Empirically Based Macroeconomics. *Middlebury College Economics Discussion Paper* No. 08-08.

Il sole24oreSanità, (2012), *Focus*, 24-30 april 2012 - pp.11-15- and 17-23 april 2012- Focus pp 9-13

Louckx, F. (2002). Patient cost sharing and access to healthcare. In Mackenback J., and Bakker M. (eds), *Reducing inequalities in health*. *A European perspective.* London: Routledge, pp 188-198

Manning, W. G., Newhouse, J. P., Duan, N., Keeler, E. B., Benjamin, B., Liebowitz, A. et al. (1988). Health insurance and the demand for medical care. Evidence from a randomized experiment. *Santa Monica, CA: RAND Corporation*, 1988. Report R-3476-HHS. ISBN 0-8330-0864-1. An abridged version of this report. was published in Manning, W.G. *et al.*(1987) Health insurance and the demand for Medical Care: evidence from a randomized experiment. *American Economic Review*, 1987, 77, 3:251-277

Ostrom, T. (1988). Computer Simulation: the Third Symbol System. *Journal of Experimental Social Psychology*, 24, 381-392.

Richiardi M., Leombruni R., Saam N. and Sonnessa M. (2006). A Common Protocol for Agent-Based Social Simulation. *Journal of Artificial Societies and Social Simulation*, 9(1). Retrieved from http://jasss.soc.surrey.ac.uk/9/1/15.html

Wagstaff A. *et al.* (1999). Equity in the finance of health care: some further international comparisons, *Journal of Health Economics*, 1999, 18, 3:263-290.