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A computational approach for the health care market

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Abstract In this work we analyze the market for health care through a computational approach that relies on Kohonen's Self-Organizing Maps, and we observe the competition dynamics of health care providers versus those of patients. As a result, we offer a new tool addressing the issue of hospital behaviour and demand mechanism modelling, which conjugates a robust theoretical implementation together with an instrument of deep graphical impact.

Keywords Self-organizing maps · Health market · Adaptive behaviour incomplete information · Mixed market

1 Introduction

The understanding of the health care market is the logical prius of any effective reform or policy, but market failures can make difficult the task.

The key issue is represented by market asymmetry of information, that avoids patients to exactly assess the actual quality of the service, even after the service has been experienced [4]. This characteristic has already been widely discussed in the literature [14, 15], where health service is referred to as a *credence good*, opposed to *search* and *experience* goods: whereas the quality of a search good is known ex ante and the quality of an experience good is known ex post, the quality of a credence good is difficult or expensive to judge even after purchase [3]: it turns then out that in order to acquire the conclusive assessment of those goods, a learning (adaptive) process needs to be implemented both by patients and providers.

A further aspect of complexity regards the supply side, where private and public hospitals, characterized by asymmetry in objectives and constraints, compete under the same conditions for patients in an environment where a third party (government agency or insurance company) pays for the treatments provided. This is for instance the typical case of countries where hospitals are reimbursed on the basis of a prospective payment scheme, i.e. a fixed price per treated patient (within a specific diagnosis group), depending on the average production cost. From the provider perspective, the health care services are characterized by uncertainty in the cost of treatment. As a consequence, the hospitals will be induced to implement a cost containment effort, and to seek for patients investing on quality, provided that patients do not directly pay for the services they receive.

In this scenario, the producer has to determine his best strategy in a very complicated game, much more than what a traditional economic model can handle.

The aim of the present paper is to draw a computational approach which is able to take into account all those features as a whole. To such aim, we will introduce a model based on unsupervised neural networks, namely on Kohonen's Self-Organizing Maps (SOMs)

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[8], arranged into two layers: in the upper layer the competition dynamics of health care providers is modelled, while in the lower level the patients behaviour is monitored. Using topological features of SOMs, interactions take place inside each level, while a voting procedure regulates the vertical flow of information between layers. In this way, signals move vertically from hospitals to patients and vice-versa, but they also spread out sideward, from patient to patient, and from hospital to hospital.

What remains of the paper is organized as follows: in Section 2 we will provide an insight into the economic model we have taken into account; Section 3 will describe the theoretical background of SOMs, Section 4 will discuss the results obtained in a case study, and, finally, Section 5 will conclude.

2 The economic model

2.1 The providers of health care services

We consider a health care system whose behaviour scheme mimicks that mostly adopted by countries having the provision of health services organized by an internal market. Inside this market,both private and public hospitals compete among themselves for patients, with revenues depending on the number of treatments provided. Within the discussed case, patients either pay or not for the health services they receive, but in both cases they will be concerned about the hospital's costs.

Focusing on the supply side, the asymmetry in the objectives and in the constraints faced by the competitors makes the understanding of their behaviour and strategy very tricky, although it is possible to fix some typical features showing the way.

The main difference among public type hospitals and private ones, for instance, may be found in the scale: public hospitals are generally large–sized, whereas private hospitals are smaller. The number of treatments that the system can offer may be therefore different: public hospitals should treat any type of patient (regardless to the cost), and any pathology; on the other hand, private hospitals might tend to specialize on those pathologies which can grant higher revenues.

Another distinctive feature resides in the way hospitals can affect their case mix by means of quality and advertising variables [13]: patients's lack of knowledge about the true relationships between care and health outcomes biases their choice that can be hence conditioned by indexes of perceived quality rather than by appropriateness and effectiveness of the services delivered by the hospital.

In a coherent way to the framework discussed in previous lines, we will assume that hospitals behaviour can be notably influenced by a number of variables:

(a) the number of treatments (*nt*). The variable *nt* is assumed to have higher values in the case of large–sized public hospitals, and lower values in the case of small–sized private hospitals, since the first ones, as already said, generally provide a wider range of treatments
(b) the quality delivered which is, in turn, made up of two components:
   - the quality for health-related services (*hqs*), i.e. those services that improve the medical quality of the care (appropriateness, health, nursing, aftercare, etc.);
   - the quality for hotel-related services (*hqns*), which comprises all those services that are not strictly medical, but still improve the patient's stay in hospital (comfort, information, kindness, catering services and so on).
(c) the level of advertising (*hadv*) by which hospitals try to affect patients behaviour, providing information about the hospital and its services. Note that the role of advertising in the health market is a consequence of the asymmetry of information: it is suitable to convey some information to patients in order to influence their behaviour; advertising is other than quality but it might inform about it.
(d) the general cost (*cgen*) borne by the hospital in order to cover all the variables described at points (a)–(c).

2.2 The patients

The way patients are represented into our model is inspired by a set of observations we are going to explain on following. Generally, each patient chooses the hospital to which he addresses his demand depending on his own preferences. In a tax financed system or even in the case of a private insurance, patients do not pay for the services they receive and their decision regarding the best provider should be mostly based on the quality level. However, because of asymmetric information the actual quality provided by the hospital might be observed with bias.

In consideration of that, we assume that patients behaviour is mainly affected by three variables:

(a) the quality mix of the services they receive, that is the share of the quality for health–related services

with respect to the share of the quality for hotel-related services;
(b) the advertising expenditure;
(c) the spatial distance, i.e. the hospital physical position with respect to the patient location.

In addition to what stated on previous rows, we also assume that patients attitude towards quality mix and advertising varies according to the patients type. In particular, we consider two type of patients, of low and high severity type, respectively: high severity patients are more interested in health quality (*hqs*), whereas the low severity patients attach importance to the hotel related services (*hqns*). Respect to the hospitals side discussed in Section 2.1, we have taken into account two additional variables: *CrepH* and *CexpH*. *CrepH* expresses the scores given by patients to hospitals reputation; as such, we have modelled it as a linear combination of the medical quality (*hqs*), of the non medical quality (*hqns*), and of the level of advertising (*hadv*):

$$CrepH = \gamma_1^i hqs + \gamma_2^i hqns + \gamma_3^i hadv \qquad (1)$$

where γ_r^i, $(r = 1, \ldots, 3)$ is the coefficient associated to each variable, being $\sum_{r=1}^{3}\sum_{i=0}^{1}\gamma_r^i = 1$, and i is a binary variable that marks patients in a different way, whether they are of low severity $(i = 0)$, or of high severity $(i = 1)$, with:

$\gamma_1^1 > \gamma_2^1 > \gamma_3^1$;

and:

$\gamma_2^0 > \gamma_1^0 > \gamma_3^0$;

The variable *CexpH*, on the other hand, represents the hospital attitude to treat high severity patients. Like in the case of *CrepH*, *CexpH* is here modelled as a linear combination of variables:

$$CexpH = \lambda_1^i hqs + \lambda_2^i nt \qquad (2)$$

where λ_s, $(s = 1, 2)$ are the weights associated to each variable, and: $\lambda_1 \neq \lambda_2$, $\lambda_1 + \lambda_2 = 1$.

3 The computational approach

Computer simulation is nowadays a key technique to model economic dynamics [2]. The current interest on such topic may be variously explained: this work is aligned to the position outlined in [7], who emphasized the importance of looking at the economy as an evolving network: interaction is then regarded as a leading aspect of economic systems.

Those considerations apply also to the case under examination, where we take into account both individuals (the patients, and to certain extent, the hospitals), and aggregate entities (group of patients). With this in mind, plausible simulations of interaction should take into account at least three interrelated levels of issue:

(a) the individual level, driven by personal interest;
(b) the aggregate level, where global behaviour not necessarily emerges as the simple cumulation from the individual stage;
(c) the level of the bi-directional flow, linking individual to aggregate behaviour, and viceversa, so that the former stage affects the dynamics of the whole, as well as the macro level, in turn, may influence the micro one.

Here we are focusing on a computational technique to model those interplays by means of unsupervised neural networks, namely, by Kohonen's SOMs.

The SOM [8] is a projection method based on the principle of space representation through dimension reduction: a finite set of input patterns is represented by means of a smaller number of nodes (neurons), sharing with inputs the same format, and arranged into a mono or bi-dimensional grid; in order to avoid hedges effects, wraparound versions can be also implemented. When an arbitrary input is presented to a SOM, a competitive procedure starts, during which a winner or leader neuron is chosen in the map, as the best matching node, according to a similarity measure (a metric) previously fixed. A generic step of the procedure may be then summarized as follows: we will refer to the case of a mono-dimensional SOM, but such layout can be easily generalized to higher dimensional grids.

If $\mathbf{x}(t) = \{x_j(t)\}_{j=1,\ldots,n} \in \mathbb{R}^n$ is the input item presented to a map M with q nodes with weights $\mathbf{w}_i(t) = \{w_{i,j}(t)\}_{j=1,\ldots,n} \in \mathbb{R}^n$, $i = 1, \ldots, q$, then i_t^* will be claimed the winner neuron at step t if and only if:

$$i_t^* = \underset{i \in M}{argmin} \left(\sum_{i \in M} \sum_{j=1}^{n} |x_j(t) - w_{ij}(t)|^p \right)^{1/p}, \quad p \in \mathbb{N} \qquad (3)$$

Note that p is typically set to 1 (city block or Manhattan distance), or 2 (Euclidean distance).

Once the leader has been identified according to Eq. 3, the correction of nodes in the map takes place; if $Neighb_{i^*}(t)$ is the set of neurons in the map belonging to the neighbourhood of i^* (in a topological sense), then:

$$\mathbf{w}_i(t+1) = \mathbf{w}_i(t) + h_{i^*,i}(t)[\mathbf{x}(t) - \mathbf{w}_i(t)] \qquad (4)$$

Here $h_{i^*,i}(t)$ is an interaction function, governing the way the nodes adjust respect to the winning neuron on the grid. Typical shapes for $h_{i^*,i}(t)$ include the constant function:

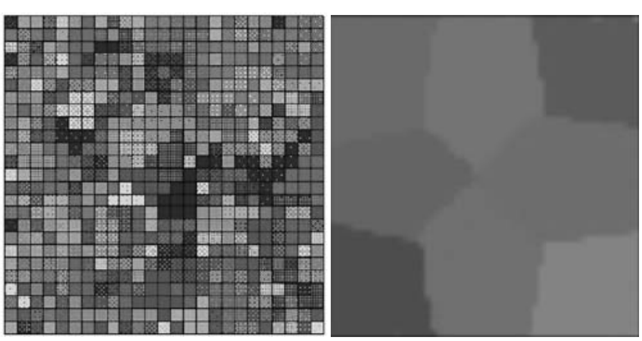
$$h_{i^*,i} = \begin{cases} \alpha \ , \ i = i^* \vee i \in Neighb_{\,i^*}(t); \\ 0 \ , \ otherwise \end{cases}$$

with $\alpha \in (0, 1)$, and the Gaussian function:

$$h_{i^*,i} = exp\left\{-\frac{\sum_{r=1}^{n}|w_{i,r}(t) - w_{i^*,r}(t)|^2}{2}\right\}$$

After iterating such procedure over a number of epochs, the map should tend to a steady organized state, and neighbouring neurons should represent similar inputs.

Figure 1 shows one of the most attractive features of SOM algorithm, i.e. its capability to produce results that may be visualised in a quite appealing fashion. To our purpose, this means the possibility to represent complex dynamics, and to visualize them into mono or bi–dimensional neural manifolds. Once the training process is concluded, in fact, SOMs can be used to visualize the multidimensional input into the mono or bidimensional grid: different colours (or shades of gray) represent nodes (neurons) with different features, while similar colour shades (gray shades) represent nodes or group of nodes (clusters) that are a projection of inputs sharing the same features.



a **b**

Fig. 1 From left to right: a 25 × 25 SOM at initial step (**a**), and after 2000 iterations (**b**). Neurons are coloured according to their similarity to neighbours. Note that the map evolves from an original disordered state (**a**) to an ordered state (**b**), with similar neurons aggregated into clusters

Additionally, whereas the SOM represents the bi–dimensional projection of a multidimensional input space, the original map may be split into as many sub-maps as the number of components of the input space itself: in this way we will look at the overall results, but we will be also able to examine the influence of single determinants on such result.

Starting from this point, in the examined case we have focused on the following issues:

- the patient behaviour and its adaptive process;
- the hospital behaviour and its responses to external input;
- the feed-back among the agents (patients and hospitals) of the market.

We have then used the SOM algorithm to develop a more complex bi–layered model, with patients and hospitals lying in two different layers: in the upper layer SOM (a $nrH \times ncH$ map), hospitals are organized and interact, while in the second layer SOM ($nrP \times ncP$), interactions among patients are observed. In the upper level, where hospitals are located, there is a dynamic competition for patients that rules out according to Eqs. 3 and 4. In the lower level map, information moves sideward from patient to patient, once again according to Eqs. 3 and 4, and patient's expectation is affected by other patients experience and judgement.

Additionally, information and signals move both upwards from patients to hospitals, and downward from hospitals to patients. In the first case, the supply side adjusts its components in order to meet the demand requirements; in the second case, as a consequence of the asymmetry of information, patients experience a learning process about the hospitals' quality and behaviour. Such vertical interaction is managed at each time t (from lower to upper layer) according to the following rule:

$$\begin{aligned} w^H_{r,s}(t+1) = \max\Bigg[& w^H_{r,s}(t), w^H_{r,s} + \frac{1}{crnk - Nc - 1} \\ & \times \left(1 - \frac{rnk}{nr}\right) \times f^H\left(CrepH_{w^H_{r,s}(t)},\right. \\ & \left. CexpH_{w^H_{r,s}(t)}\right)\Bigg] \end{aligned} \tag{5}$$

with $r = 1, \ldots, nrH$; $s = 1, \ldots, ncH$. More in detail, $w^H_{r,s}$, is a generic neuron in the upper map, while $crnk$ is the cluster ranking in the lower map, Nc is the number of clusters in the lower map, rnk is the cluster ranking in the upper map, nr is the average number of elements for each cluster, and, finally, $f^H(CrepH_{w^H_{r,s}(t)}, CexpH_{w^H_{r,s}(t)})$ measures the influence on each hospital operated by *CrepH* and *CexpH*:

$$f^H\ (CrepH_{w^H_{r,s}(t)}, CexpH_{w^H_{r,s}(t)}) = \frac{1}{nrP \times ncP} \frac{\sum_{v=1}^{nrP}\sum_{z=1}^{ncP} CrepH_{w^H_{r,s}(t)} + CexpH_{w^H_{r,s}(t)}}{\sum_{k=1}^{NelH} w^H_{r,s}(t)}$$

where *NelH* is the length of nodes in the hospitals layer. From the practical standpoint Eq. 5 means that hospitals are not only influenced by the competition among themselves, but also by the evolving ranking that patients make about hospitals, and by the influence expressed in such process by hospitals reputation and hospitals ability to treat high severity patients. In a similar way, downward interaction is managed according to the:

$$w^P_r(t+1) = \max\left[w^P_r(t), w^P_r(t) + \left(1 - \frac{rnk}{nr}\right) \times f^P\left(CrepH_{w^P_r(t)}, CepxH_{w^P_r(t)}\right)\right] \quad (6)$$

Here $f^P(CrepH_{w^P_r(t)}, CepxH_{w^P_r(t)})$ represents the conditioning expressed by hospitals on patients, and it is given by:

$$f^P\ (CrepH_{w^P_{r,s}(t)}, CexpH_{w^P_{r,s}(t)}) = \frac{1}{nrP \times ncP} \frac{\sum_{v=1}^{nrP}\sum_{z=1}^{ncP} CrepH_{w^P_{r,s}(t)} + CexpH_{w^P_{r,s}(t)}}{\sum_{k=1}^{NelP} w^P_{r,s}(t)}$$

where *NelP* is the length of nodes in the patients layer.

4 Case study

We have studied the behaviour of the model presented in Section 3, using a 10×10 SOM for the upper layer, with nodes components representing the 5 variables outlined in Section 2.2, as those affecting hospitals behaviour. An overall number of 200 input patterns (i.e. hospitals) have been used to train the map. Such inputs have been built in order to represent various types of hospitals, diversified according to the number of offered treatments, advertising costs, and services (health and non-health related) quality.

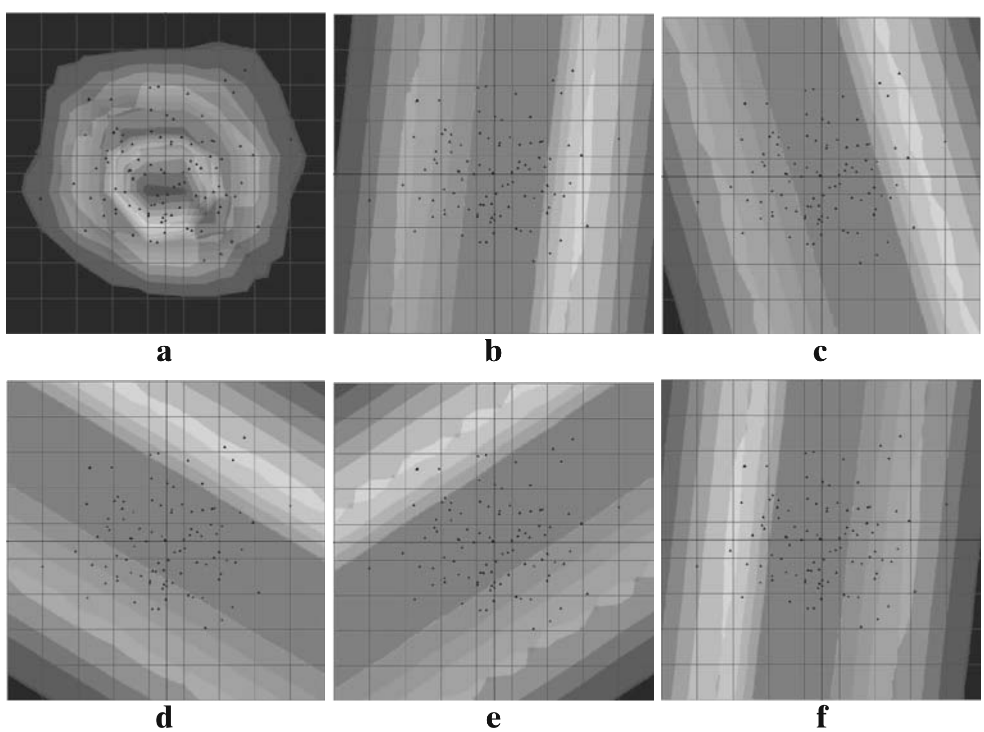


Fig. 2 From left to right, and from top to bottom: hospitals overall density (**a**), and density related to the behaviour of variables *Hqs* (**b**), *Hqns* (**c**), *Hadv* (**d**), *Hgen* (**e**), *Hnt* (**f**)

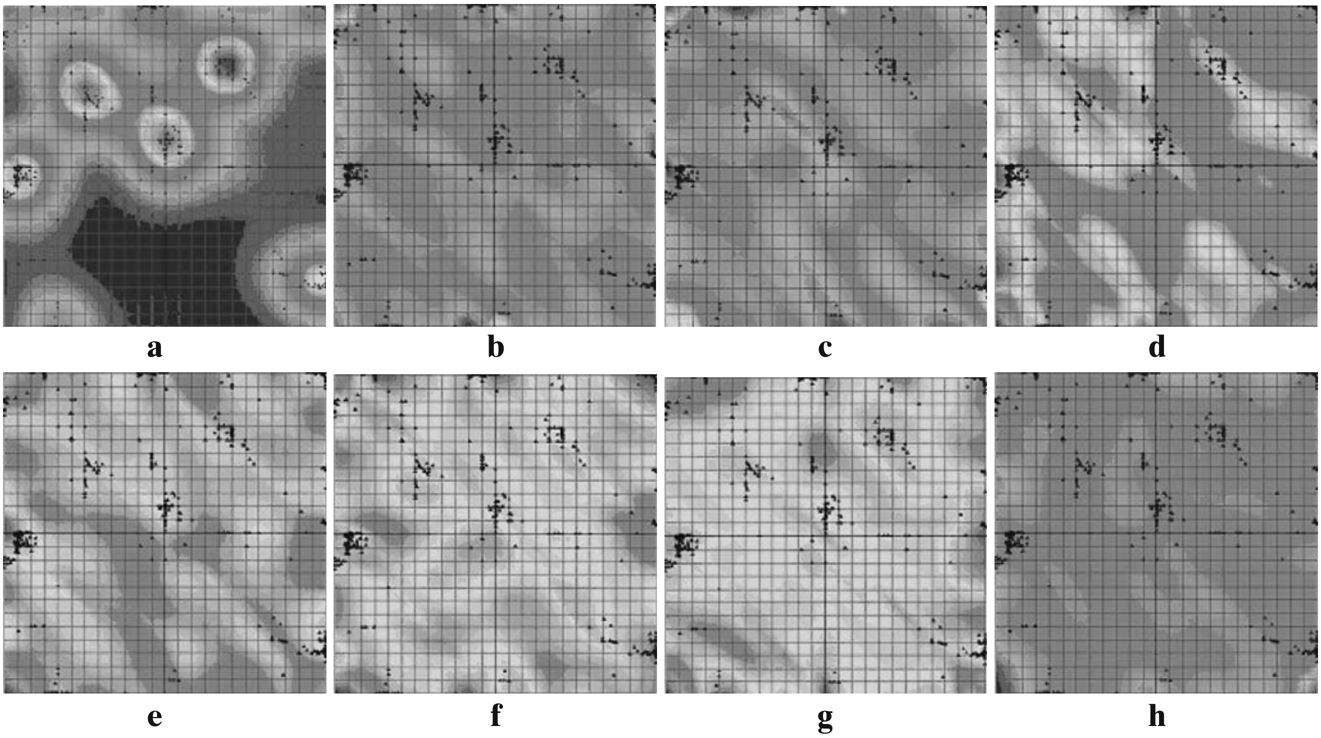


Fig. 3 From left to right, and from top to bottom: patients overall density (**a**), and density related to the behaviour of variables *Cqs* (**b**), *Cqns* (**c**), *Cadv* (**d**), *Cgen* (**e**), *Cnt* (**f**), *CexpH* (**g**), *CrepH* (**h**)

The lower layer SOM has been built wider than in the case of hospitals: here we have managed a 25×25 SOM with 7–dimensional nodes, for an overall number of 2000 input patterns (patients). The greater number of components (7 instead of 5) is simply due to the greater number of variables affecting patients behaviour, as said in Section 2.2.

Figure 2 shows the organization of the hospitals input space: various gray shades represent different variable values: in particular, brighter gray tones represent lowest values; moving from them to harder shades of gray we will also move towards higher values.

Figure 3, on the other hand, represents the dynamics of patients organization. In this case, we have taken into account the evidence that generally a greater number of patients share a reduced number of hospitals offering cares and services.

Looking at the simulation results, one can observe that hospitals tend to uniformly set to a homogeneous optimal size. In particular, this is evident in Fig. 2f which refers to the number of treatments *nt* with the brightest shades of gray to represent middle size hospitals, whereas the darkest tones indicate large size: looking at the distribution of points in the map, hospitals converge to a middle size, i.e. they reach better financial results (that means lower costs) when they are able to provide an intermediate number of treatments respect to the extrema of the fully specialized hospital (which provides only a single treatment) and of the generic hospital that furnishes the whole variety of treatments.

Another interesting information is related to the analysis of the behaviour of variables *Cqns* and *Cadv*: higher values for *Cqns* and *Cadv* are associated to lower general costs *Cgen*. According to such observation, hospitals should sustain costs that influence only the quality of health–related treatments: the higher they are, the higher the effects on hospitals reputation, even without changing anything in the quality of non–health service. In practice, those results suggest that some mystifying actions on the effective level of the quality of services are possible to the extent of the imitation component which is inside the neighbourhood structure of the map. This is not trivial, especially if we think that it is the outcome of a procedure completely data–driven.

5 Conclusive remarks

This study examined a computational approach to model the behaviour of the health care market. The ratio was that to introduce a tool of analysis which is suitable to provide insights concerning the interactions among hospitals and patients, to be read both by economists and health managers.

To this purpose, hospitals and patients have been modelled by a learning/adaptive process by means of unsupervised neural networks, namely with SOMs. We managed a model made up by two SOMs arranged into two layers, one representing hospitals, and one representing patients. In such depicted settings, hospitals compete among themselves, and take into account and react to external signals expressed by a feedback with the patients layer.

We have then studied a fictitious environment including hospitals with various size (and degrees of specialization). Patients, in turn, have been clustered according to different severity types.

The simulation results offer some interesting information, because they seem to incorporate either positive elements of a demand driven mechanism, or negative ones. In particular, we refer to the risk that the market structure may induce hospitals to curb the medical quality level (avoiding the case of malpractice) with a consequent social loss.

In our opinion, our model fits to provide insights to analyse the implications for health quality, hotel related quality, cost and advertising of the proposed market structure and to understand the welfare implications of the different scenarios. The introduction of a new policy should evaluate the ability and the potential to save and improve quality in the market. Any government policy intended to provide incentives to competition would seek first to identify the quality variable and its outcome level when competition among providers is implemented in the market of interest. Thus the second step would consist on determining (by simulation) the best market structure so as to advance quality and generate appropriate mix among quality, advertising and efficiency.

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