



The Effects of Defensive Medicine in Physician–Patient Dynamics: An Agent-Based Approach

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Abstract

We analyze different scenarios of defensive medicine in a novel framework based on game theory and network analysis, where links in the network represent healing relationships between a physician and a patient. The physician should choose between providing the optimal treatment or an inferior one, which can amount to practicing defensive medicine. The patient should choose whether to litigate or not if an adverse event occurs. A major result of such analysis is that the steady state does not depend on the litigiousness of the initial system or the initial distribution of strategies among physicians or the distribution of patients over physicians. Moreover, reaching a virtuous steady state or an entirely defensive one appears to be independent of the fact that patients take into account the quality of treatments directly or they rely merely on popularity when choosing their physicians.

Keywords Defensive medicine · Game theory · Network dynamics

1 Introduction

The Office of Technology Assessment defines defensive medicine (DM) as follows: *Defensive medicine occurs when doctors order tests, procedures, or visits, or avoid high-risk patients or procedures, primarily (but not necessarily solely) to reduce their exposure to malpractice liability. When physicians do extra tests or procedures primarily to reduce malpractice liability, they are practicing positive defensive medicine. When they avoid certain patients or procedures, they are practicing negative defensive medicine.*

This practice can expose patients to the risk of harm from inappropriate procedures, and the healthcare system to a substantial increase in costs [29, 34, 41]. Health issues include, among others, the excessive use of Caesarean section to deliver babies and the excessive exposure to radiation in diagnosis [19, 26]. Defensive medicine in high-risk specialities is

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a worldwide issue. In the USA, 93% of respondent physicians reported practising it, while comparable numbers emerged in Europe, China, and Japan [25, 27, 40, 44].

Much has been written about defensive medical practice. We can try to classify the literature on defensive medicine under two lines of researches: empirical studies and theoretical literature. The former line consists of collecting empirical data to investigate physicians' views and experiences in relation to hedging-type defensive medical practice. Cross-sectional surveys are the most common method of data collection (see among the others [11, 24, 30, 40, 42]). The latter, almost exclusively through static or multi-stage models (see among the others [1, 6, 13, 17–19, 21, 32, 33, 36, 39]).

In more recent years, some authors have tried to model the interaction between physicians and patients using game theory and dynamical models. In [45], the authors contribute to theorize the physician–patient relationship based on game theory and analyze the current situation and influencing factors for medical disputes among different hospitals. The authors observe that relationships between physicians and patients have become worse increasingly, whereas physician–patient disputes or conflicts and their compensation have aggrandized year by year. The game relationship of physician–patient is a noncooperation, dynamic and incomplete information game, and the advantages of cooperation are far greater than the competition between doctors and patients. Therefore, it is necessary to take targeted measures to prevent and control the medical disputes by establishing a harmonious physician–patient relationship in different levels of medical institutions.

The game-theoretic approach proposed by [2–5] studies the behavioral choices of physicians and patients, and their dynamics in continuous time (replicator dynamics), in large populations of agents who repeatedly engage in healing interactions. In particular, in [2] the focus is on positive defensive medicine when additional services are offered to discourage patients from filing malpractice claims, or to convince the legal system that the standard of care was met. On the other hand, the authors in [3] consider negative defensive medicine, that is the case in which physicians tend to avoid a source of legal risk, e.g., by adopting safer but less effective treatments. In [5], the authors analyze different scenarios of defensive medicine in a unique game theoretic framework, representing a healing relationship between a physician and a patient. They obtain four scenarios representing the positive and negative forms of defensive medicine, with or without physician's moral hazard, where legal parameters can have opposite effects on the probabilities that physicians practice defensive medicine and that patients litigate, depending, respectively, on the form of defensive medicine and on the presence of moral hazard. In [4], the authors analyze, in the context of the evolutionary game, how physicians may prevent negligence charges by practicing defensive medicine or by buying medical malpractice insurance. The latter choice transfers the risk of litigation from the physician to the insurer.

In addition, there is no lack of applications of network analysis to the study of networks of physicians or patients. In [37], it is leveraged to reconstruct unipartite networks of physician–physician connections based on shared patients. Their main findings are that constructing physician networks around shared episodes of care is a clinically sound alternative to previous approaches to network construction that does not require arbitrary decisions about thresholding. The resulting networks capture somewhat different aspects of patient–physician encounters. The authors in [31] study how professional networks among physicians vary across geographical regions, and which factors characterize their mutual connections. They conclude that network characteristics vary across geographic areas and that physicians tend to share patients with other physicians with similar physician-level and patient-panel characteristics. In [9], the authors investigate the variation in the rate of hospital admissions for ambulatory care-sensitive conditions across different physician networks and the

underlying network characteristics. They observe that networks with a higher percentage of primary-care physicians and networks in which patients received care from a larger number of physicians had higher ambulatory care-sensitive rates.

It has been recognized that peer networks can influence decision-making by physicians thorough a complex contagion mediated by social reinforcement [10], and that an association exists between peer connectedness among physicians and the diffusion of emerging medical technologies [43]. The effects of patient connectedness on measures of physician performance have also been addressed in [7]. On a different level, network science tools have been exploited to define the notion of referral paths encoding the chronological sequence of physicians encountered by a patient [12]. These studies appear to focus on unipartite networks of physicians or patients.

To complete this brief overview of the literature, it is worth mentioning that recently some authors have related defensive medicine not only to the fear of litigation, but also to the fear of being perceived as a low-profile physician among colleagues and/or patients [22, 23, 28]. Loss of reputation in the workplace can lead to “shame” far beyond guilt about a specific error, potentially leading to professional burnout [14]. This can be further boosted by a community culture oriented to individual blame, that publicly stigmatizes physicians for medical errors through the mass media [38].

We believe that the issue of reputation is an interesting aspect to analyze in the context of physician–patient behavior. Moving from the “positive defensive medicine game” described in [2, 3], in this work we attempt to make a further contribution to the theoretical literature on the behavioral aspects of patient–physician relationships. We do that by modeling their interactions directly as a time-varying bipartite network of interacting agents (see Sect. 2.2). We analyze defensive medicine behavior introducing the concept of “reputation” (see Sect. 2.1) for physicians as an index that characterizes the physician–patient market.¹ We explicitly model the system as a bipartite network where connections form whenever a patient receives a treatment from a physician. Reputation can be defined in various ways. We can think of it as an objective measure of the average benefit for patients. If so, it will generally depend on factors like the physician’s personal skills and the clinical risk of the treatment. It may also be an index of popularity of some sort, like the physician’s degree centrality in the network or a possibly more elaborated index of vertex centrality [8, 35]. Different definitions represent different attitudes of patients and different levels of information. Independently of its specific definition, we assume that “reputation” (see Sect. 2.1) is an index based on which patients choose which physician to link with. The patient allocation dynamics is modeled jointly with the dynamics of agents’ strategic interactions based on their payoffs. The latter dynamics depends on the exogenous parameters that characterize the treatments and the legal system, as well as on the network connectivity pattern.

On one hand, we aim at identifying conditions for a virtuous system in which most physicians provide the optimal, non-defensive treatment, and to test how much a virtuous steady state is achievable under high litigiousness conditions. We also try to find out the parameters that are effective in steering the network’s state and that can be adjusted by regulators, at least in principle. On the other hand, we are interested in highlighting path dependence phenomena, if any, i.e., how the initial distribution of strategies (and clients)

¹ We do not discuss here the role of price competition. We focus on the social mechanisms that mediate allocation of patients to physicians during the game. Allocation is based on word of mouth and thus on the reputation that physicians have within the community. Accordingly we model the institutional framework as not market oriented, in such a way that the prices of medical services do not influence the patient’s choices. In other words, there is no competition between physicians on the services offered or we can think that patients are willing to spend according to the saying “being healthy comes first.”

affects the final outcome, and in measuring the effects of patients' preferences toward better performing or simply more popular physicians.

An opinion of the authors is that a framework combining network dynamics with a game-theoretic approach can be particularly helpful to model medical systems. The two approaches are well matched because they share two common assumptions about social behavior that make their combination intuitively appealing. The first is that participants recognize one another as being players, or actors, in the game. Secondly, in both game theory and network science contexts, agents often have incomplete information regarding the strategies of the other agents and their mutual connections. This is an important trait since organizations and individuals often display less than perfectly rational behavior, because they lack the information to do otherwise. Therefore, game theory and network science taken together can investigate coalition participants' actions and strategies in a meaningful way [20].

We believe that a network dynamics model based on individual strategic interactions and reputation-based attachment rules can provide a robust agent-based framework to investigate emergent behaviors in medical systems. To the best of our knowledge, this study is the first of its kind in the literature. We believe it may provide relevant information and insights for policy makers about the effects of different reforms and enable further analysis by academics and practitioners as well. At the same time, the theoretical model and the analyses presented here are meant to provide generic indications and do not try to reproduce any empirical facts by the previous literature.

The paper is organized as follows. The model and the assumptions regarding defensive medicine are presented in Sect. 2. The simulation setup is described in Sect. 3 and discussed in Sect. 4. Finally, in Sect. 5 we draw our conclusions.

2 The Model

2.1 Agent Strategies

We model the system as follows. At discrete times $t = 1, 2, \dots$, a large number of interactions between physicians and patients take place. Every interaction consists of a patient receiving medical treatment from a physician. Such a treatment guarantees the patient a certain benefit b with a probability q to also provoke a damage h . The stochastic net benefit for the patient is then $B = b - I_h h$, where I_h is 0 or 1 when the treatment has a positive or negative outcome, respectively, and $h > b$ in order for B to be negative for a negative outcome. Physicians can choose to provide either of two treatments: one that can determine a greater benefit but has a higher probability to produce a negative outcome and result in a damage for the patient, and another with a reduced benefit but also lower intrinsic risk. We indicate the latter strategy by D, for “defensive treatment,” and the former by ND for “non-defensive.” Every treatment supplied produces a certain benefit b^{ph} for the physician too. Damaged patients may file a lawsuit against their physicians, which implies a cost c in terms of legal expenses. The damaging physician is judged guilty in court with a probability p that depends on the treatment. A guilty physician must compensate the patient for an amount k . Patients that file a lawsuit when damaged are said to play strategy L, from “litigious,” while patients that do not are said to play strategy NL.

Thus treatment D has associated parameters $b_D, q_D, h_D, p_D, c_D, k_D$, while parameters $b_{ND}, q_{ND}, h_{ND}, p_{ND}, c_{ND}, k_{ND}$ characterize treatment ND. Two conditions qualify a treatment as defensive. It must be $q_{ND} > q_D$ (higher clinical risk) and we also assume $\mathbb{E}[B_{ND}] > \mathbb{E}[B_D]$,

meaning the non-defensive treatment has higher expected benefit. In this sense, treatment ND is to be considered the optimal treatment in medical terms. A perfectly efficient system should incentivize the optimal treatment and discourage defensive medicine. In terms of legal parameters, this would correspond to $p_D = 1$ and $p_{ND} = 0$ which is clearly an abstraction. More generally we only require the probability of being found guilty to be larger for D physicians, $p_D > p_{ND}$.

We use the term “agent” to refer indifferently to a patient or a physician, or when context makes clear to which category they belong. We assume that agents decide which strategy to play *ex-ante* before each treatment, and that they have no information about each other’s strategy. We also assume that their behavior is uniform, meaning that physicians play the same strategy in the treatment of all their patients, and that patients adopt the same strategy independently of who is the specific physician that treat them at a given time. This is coherent with the idea that agents choose their strategies *ex-ante*. Agents within the two categories are homogeneous. At any given time, they may be distinguished only by strategy.

We assume that the initial populations feature fractions f_D and f_L of D-physicians and L-patients, respectively, and $f_{ND} = 1 - f_D$ and $f_{NL} = 1 - f_L$ of ND-physicians and NL-patients. The conditional expectation of patient net benefits is $\mathbb{E}[B] = b - qh$ so that the difference between the treatments reads

$$\mathbb{E}[B_{ND}] - \mathbb{E}[B_D] = (b_{ND} - b_D) - (q_{ND} h_{ND} - q_D h_D) \quad (1)$$

As long as physicians’ strategies are uniform, the values $\mathbb{E}[B_D]$ and $\mathbb{E}[B_{ND}]$ also represent the expected “performance” of a physician who plays strategy D and ND, respectively.

We indicate by Π^{ph} and Π the (stochastic) payoff of physicians and patients. In the limit where patients are connected to physicians randomly at the beginning of the observation period, the conditional expectations of physicians’ payoffs are $\mathbb{E}[\Pi^{\text{ph}}] = b^{\text{ph}} - f_L p q k$ and their difference is

$$\mathbb{E}[\Pi_{ND}^{\text{ph}}] - \mathbb{E}[\Pi_D^{\text{ph}}] = (b_{ND}^{\text{ph}} - b_D^{\text{ph}}) - f_L (w_{ND} k_{ND} - w_D k_D) \quad (2)$$

where $w_D = p_D q_D$ and $w_{ND} = p_{ND} q_{ND}$.

Similarly, for the difference between the conditional expectations of the patients’ payoffs, we obtain

$$\mathbb{E}[\Pi_{NL}] - \mathbb{E}[\Pi_L] = q_D f_D (c_D - p_D k_D) + q_{ND} (1 - f_D) (c_{ND} - p_{ND} k_{ND}) \quad (3)$$

We notice that the previous expression contains neither the benefits b_D , b_{ND} , nor the damages h_D , h_{ND} .

For the sake of clarity, in the rest of the paper we will assume that the two treatments can procure equal damages ($h_{ND} = h_D = h$) and have the same associated compensations and legal costs ($k_{ND} = k_D = k$, $c_{ND} = c_D = c$).

2.2 Network Dynamics

Bipartite graphs represent a widely used tool to describe associations between two groups, ranging from social networks of affiliations to networks of financial holdings [15, 16]. Game theory allows us to model the strategic interactions between physicians and patients in terms of their payoffs, and the network framework usefully captures the structure of the web of interactions that form, varying with time, as a result of both the agents’ strategies and the patients’ preferences in the physician selection process. The agent-based approach also allows us to model the possibly different timescales that characterize the dynamics of strategy

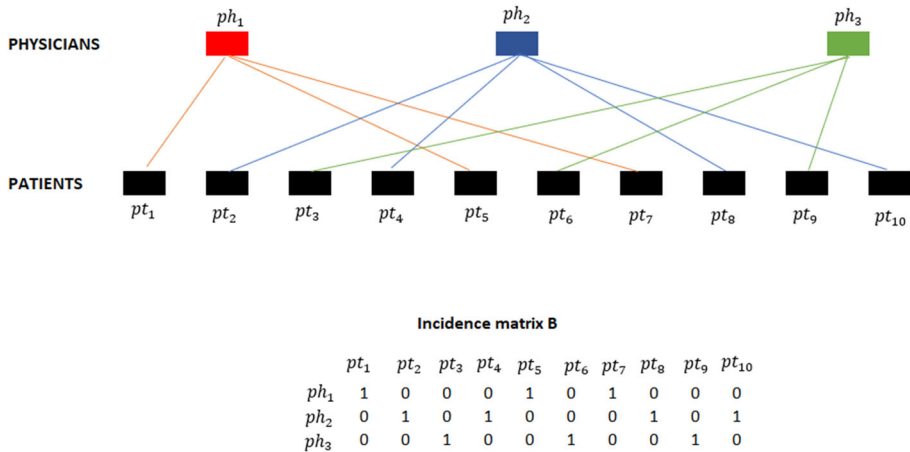


Fig. 1 A bipartite network of $m = 3$ physicians and $n = 10$ patients (ph, physician; pt, patient) (Color figure online)

revision and patient–physician link formation. The agents’ strategies and behaviors reflect the relation between positive defensive medicine and litigiousness and also account for the interplay between strategies and the establishment of patient–physician relationships.

At the beginning of every period t , each patient is connected to exactly one physician that provides the medical treatment by the end of the period. Let m be the number of physicians and n the number of patients in the system, with $m < n$. The information about the interactions-to-be between physicians and patients can be conveniently encoded in a bipartite graph $B(t)$. The graph’s incidence matrix (B_{ij}) is an $m \times n$ real matrix with $B_{ij}(t) = 1$ when patient j is treated by physician i during period t , and 0 otherwise. In Fig. 1, we picture the bipartite graph of a very small network, together with the corresponding incidence matrix.

The graph is disconnected and the vertices of each connected component correspond to one physician together with the patients they treat along that period of time. By the end of the period, every patient receives exactly one treatment (one-shot game). Depending on the outcome, or the realized *ex-post* benefit, patients are free to change their physicians. As a consequence, at the beginning of the next period the graph will have changed. As a simple rule, we assume that patients decide whether to leave or not based on the comparison between the realized value of B and some index of average benefit I_p at the systemic level. A reasonable choice for I_p at end-of-period is the following

$$I_p = \frac{n_D b_D + n_{ND} b_{ND} - h(n_{h,D} + n_{h,ND})}{n} \quad (4)$$

where n_D , n_{ND} , $n_{h,D}$ and $n_{h,ND}$ are the numbers of patients that have received treatment D, treatment ND and that have been damaged by either of the two treatments, respectively. Such definition for I_p simply corresponds to the arithmetic mean of the realized benefits. Approximating $n_{h,D}/n_D \simeq q_D$ and $n_{h,ND}/n_{ND} \simeq q_{ND}$ for $n_D, n_{ND} \gg 1$, we have

$$I_p \simeq \frac{n_D}{n} \mathbb{E}[B_D] + \frac{n_{ND}}{n} \mathbb{E}[B_{ND}] \quad (5)$$

So, for large numbers of treatments of both kinds, I_p approximates the weighted average of expected benefits. For a given physician i , a similar index can be defined to measure its individual performance, $I_i = (n_i b - n_{h,i} h)/n_i$.

In principle, a patient j is expected to change physician if $B_j < I_p$ (inefficient treatment) and to stay otherwise. Realistically a patient will not change immediately after receiving an inefficient treatment because of inertia. We can expect that a patient accumulates a number of inefficient treatments before getting over such inertia and leave. In this sense, we assume that the conditional probability, having accumulated u consecutive inefficient treatments, of leaving in the next time period has the form

$$P_{|u} = 1 - e^{-\alpha u} \quad (6)$$

where the parameter α quantifies inertia. We call this parameter the patient's *susceptibility*. Patients with very small susceptibility would never change their physicians even after many inefficient treatments, while highly susceptible patients are likely to leave even after one, possibly occasional, unsatisfying treatment. The unconditional probability of leaving after a number of inefficient treatments less than or equal to u is $P_{\leq u} = 1 - \prod_{\tau=1}^u (1 - P_{\tau}) = 1 - e^{-\frac{\alpha}{2}u(u+1)}$ and the unconditional probability of leaving after exactly u unsuccessful treatments reads

$$P_u = P_{\leq u} - P_{\leq u-1} = e^{-\frac{\alpha}{2}u(u+1)} (e^{\alpha u} - 1) \quad (7)$$

The previous probability is normalized and we have $P_0 = 0$ and $\lim_{u \rightarrow \infty} P_u = 1$ as required. From the expression of P_u , we can estimate the expected value $\sum_u u P_u$, namely the expected number of consecutive unsuccessful treatments after which a patient is expected to move. This value, call it τ_{α} after rounding to an integer, represents the time scale of the process of patient reallocation.

The condition $B_j < I_p$ may be realized for $B_j > 0$, and it holds automatically in case of damage ($B_j < 0$), as long as we assume that $\mathbb{E}[B_D] > 0$ and $\mathbb{E}[B_{ND}] > 0$. Damage can be considered an especially unfavorable event that may well overcome inertia. It would not seem unreasonable for a damaged patient to change regardless the past records of treatments. Because of that we assume damaged patients to leave with probability equal to 1 and undamaged patients to leave with the probability (6) if $B_j < I_p$. When a patient leaves, they choose a new physician among those that have registered a good performance in the previous period, namely those with $d_i = I_i - I_p \geq 0$. Reallocation of the patients occurs randomly with probability weights proportional to the (positive) difference d_i , so that best performing physicians have highest probability to attract new patients.

In the updating process, a physician may lose all their patients. With a slight abuse of terminology, we call *inactive* any physician with a number of patients below a small threshold n_{\min} . Otherwise we say that a physician is *active*. As a limit case and by definition, 0-patient physicians register null payoff and performance, and $d_i < 0$ at the end of the one-shot game. To avoid an unrealistic scenario where 0-patient physicians get excluded by the game indefinitely, we allow them to acquire new patients with a minimum probability during subsequent iterations. We also assume that physicians can not treat more than a given number n_{\max} of patients, either because of practical limitations or because a limit is enforced by regulators.

2.3 Strategy Revision

Between games, agents are allowed to change their strategies. Such revision of strategies is driven by the agents' payoffs. Average systemic indices can be computed for physician and

patient payoffs in the same spirit of (4):

$$\overline{\Pi}^{\text{ph}} = \frac{n_{\text{D}} b_{\text{D}}^{\text{ph}} + n_{\text{ND}} b_{\text{ND}}^{\text{ph}} - n_{\text{L,h}} k}{n} \quad (8)$$

$$\overline{\Pi} = \frac{n_{\text{D}} b_{\text{D}} + n_{\text{ND}} b_{\text{ND}} - n_{\text{h}} h - n_{\text{L,h}} c + n_{\text{L,win}} k}{n} \quad (9)$$

where $n_{\text{L,h}}$ is the number of damaged patients that play L and file a lawsuit, and $n_{\text{L,win}}$ is the number of those that win in court.

Every time the realized payoff of the agent is lower than the corresponding systemic average, that agent is expected to switch strategy. As for the process of reallocation, we suppose that strategy revision is somewhat inertial. Each agent can tolerate a below-the-threshold payoff for a number of consecutive times and the probability of switching strategy after consecutive low payoffs has the same form of (7). We distinguish the exponent of the probability function of strategy revision by the letter β and we will have two different parameters, β for patients and β^{ph} for physicians. We will refer to them as the agents' *reactivity* because they provide a measure of how swift an agent's reaction is to a sequence of poor results in terms of their payoffs, where the reaction consists in the act of switching strategy. Correspondingly, we have two time scales for the process of strategy revision, call them τ_{β} and τ_{β}^{ph} , corresponding to the rounded expected values of u , for P_u given by (7) with β and β^{ph} replacing α .

2.4 Information Set and Social Interaction

It is worth summarizing the information set available to the agents. As stated in Sect. 2.1, strategies are chosen *ex-ante* with no information about each other's strategy. In this sense, an agent's information is substantially incomplete. Agents also ignore each other's reactivity or susceptibility.

On the other hand, the network dynamics assumes that patients have access to I_{p} , based on which they choose whether to leave or stay, and to I_i for $i = 1, \dots, m$, because the probability of a new physician to be chosen by a changer is proportional to $I_i - I_{\text{p}}$. As for the strategy revision process at the end of each one-shot game, it is assumed that patients know the average patient payoff $\overline{\Pi}$ and that physicians know $\overline{\Pi}^{\text{ph}}$. These assumptions regarding the information available to agents can be justified in terms of the social connections that always exist between patients, as well as between physicians. For instance, we can imagine the "performance index" for physician i to result from an average of the perceived benefits reported by that physician's patients to each other. Indeed, each patient is likely to have acquaintances among the patients that are treated by their very same physician. Probably they also have acquaintances among patients of other physicians, who also report about their degree of "satisfaction" or perceived benefit from the received treatments, resulting in a systemic indicator like I_{p} . A similar interpretation can be attached to individual and systemic payoffs and also a network of acquaintances among physicians is expected to exist and influence their strategies. In this work we address exclusively the bipartite network formed by the individual patient–physician treatments and we renounce to model explicitly the social networks corresponding to the patterns of patient–patient or physician–physician acquaintances. We tacitly assume they exist and can effectively convey a measure of reputation for a physician and of average benefit of provided treatments. Such indices are endogenous

estimates, collectively formed by agents thorough their connections to one another even though such unipartite links are not explicitly represented.²

In the model, reallocation is driven by realized benefits. However, it is known the role that recommendations and popularity may play in determining attractiveness, and manifesting preferential attachment phenomena and “rich get richer” effects. Besides the benefit-driven model, we consider a network where patient reallocation is driven by physician “popularity” as simply measured by the number of their patients n_i and the probability for any physician to be chosen by a leaving patient is given by a linear preferential attachment rule $P_i = n_i / \sum_j n_j$. This corresponds to a system where the choice of physician is uncoupled from the dynamics of strategy revision, which in turn is driven by payoffs. For comparison, we also consider a mixed case where benefit-based reallocation is modulated by physician popularity. This translates into an attachment probability $P_i \propto d_i \times n_i$ for a physicians that has $d_i = B_i - I_p \geq 0$, while below-the-threshold physicians only lose patients.

3 Simulations Setup

3.1 Scenarios

We simulate the dynamics for a network of $m = 200$ physicians and $n = 5 \times 10^4$ patients, with parameters as in Table 1 corresponding to three scenarios.

- Scenario A (initial populations feature fractions: $f_D = 0.5$ and $f_L = 0.5$; probability of non-defensive treatment causing damage: $q_{ND} = 10^{-1}$) corresponds to a balanced network where the strategies D and ND are present in equal proportions within the population of physicians, as are the strategies L and NL within the population of patients. Treatment ND has 10% clinical risk while treatment D is considerably safer with $q_D = 0.001$. For this case, we have $\mathbb{E}[\Pi_{ND}] > \mathbb{E}[\Pi_D]$, see Table 2, so that strategy ND is favored by physicians. The expected payoff of litigious and non-litigious patients are similar. This scenario is considered a benchmark case of a “virtuous system,” with respect to which we derive the alternative cases B and C.
- Scenario B (initial populations feature fractions: $f_D = 0.5$ and $f_L = 0.9$; probability of non-defensive treatment causing damage: $q_{ND} = 10^{-1}$) corresponds to a highly litigious network, where parameters b_{ND}^{ph} and p_{ND} are chosen in order to discourage non-defensive medicine (see Table 1). Here, the expected payoff of defensive physicians is larger than that of their non-defensive colleagues, and a litigious behavior by patients is initially favored.
- Scenario C (initial populations feature fractions: $f_D = 0.5$ and $f_L = 0.9$; probability of non-defensive treatment causing damage: $q_{ND} = 0.4$) is a highly litigious one where the non-defensive treatment has a very high intrinsic risk. This is to be considered a limit case where the expected benefit from treatment ND is similar to that from treatment D. This time, litigiousness is discouraged by triplicating legal expanses and reducing compensations by a factor of ten. Correspondingly, physicians favor treatment ND as in A, while the payoff of litigious patients is roughly one half of their non-litigious counterparts.

In all cases, it is $\mathbb{E}[B_{ND}] > \mathbb{E}[B_D]$ as required by the definition of non-defensive treatment. The patients’ susceptibility is $\alpha = 0.01$, corresponding to a time scale $\tau_\alpha = 13$ for

² Such social networks of patients and physicians are not to be confused with the two unipartite projections of the bipartite network of physician–patient treatments modeled here.

Table 1 Parameters of the considered scenarios

Models	Network		Treatments							Lawsuit			
	f_D	f_L	b_D	b_{ND}	h	q_D	q_{ND}	b_D^{ph}	b_{ND}^{ph}	p_D	p_{ND}	c	k
A	0.5	0.5	1	3	5	10^{-3}	10^{-1}	1	2	0.5	10^{-2}	1	30
B	0.5	0.9	1	3	5	10^{-3}	10^{-1}	1	1.01	0.5	0.25	1	30
C	0.5	0.9	1	3	5	10^{-3}	0.4	1	2	0.5	10^{-2}	3	10

It is assumed $h_D = h_{ND} = h$, $c_D = c_{ND} = c$ and $k_D = k_{ND} = k$

Table 2 Expected benefits and payoffs at $t = 0$

Models	Benefits		Payoffs			
	$\mathbb{E}[B_D]$	$\mathbb{E}[B_{ND}]$	$\mathbb{E}[\Pi_D^{ph}]$	$\mathbb{E}[\Pi_{ND}^{ph}]$	$\mathbb{E}[\Pi_L]$	$\mathbb{E}[\Pi_{NL}]$
A	0.995	2.5	0.992	1.985	1.72	1.748
B	0.995	2.5	0.986	0.335	2.08	1.748
C	0.995	1.0	0.996	1.964	0.419	0.998

reallocation. We fix the minimum number of patients below which a physician gets classified “inactive” to $n_{\min} = 0.01 \times n/m$ (1% the average number number of patients per physician). As for the maximum number of patients a physician is allowed to treat, we set $n_{\max} = 10 \times n/m$. As for the process of strategy revision, we first assume it to have the same scale of reallocation and accordingly we set $\beta = \beta^{ph} = \alpha$. This assumption will be partly relaxed when performing comparative statics on β^{ph} .

To study the model’s dynamics and compare the different scenarios, we focus our attention on some fundamental functions. At the most basic level, the dynamics leads some patients to change physician. Depending on the parameters, some physicians may end up having less than n_{\min} patients, becoming “inactive.” We indicate as $f_{in}(t)$ the fraction of inactive physicians. Since all agents are allowed to change their strategy, the fractions $f_D(t)$ of (active) defensive physicians and $f_L(t)$ of litigious patients are of major interest. In a general setting, the distribution of strategies among physicians and the distribution of patients that receive the defensive and the non-defensive treatments are independent to some degree. Thus we also compute the fraction $f_D^{pat}(t)$ of patients that get treatment D at a given time.

The values of all the functions are computed as Monte Carlo averages after simulating the dynamics for $n_{MC} = 360$ random replicas of the initial network. Simulations are performed with a maximum of $T_{\max} = 150$ time steps and stop after that any of the populations of D- or ND-physicians become extinct.

3.2 Initial Network State

We first simulate the endogenous dynamics with benefit-driven reallocation in a network where patients are assigned to physicians at random at $t = 0$, independently of the agents’ respective strategies. This corresponds to a homogeneous initial network of physicians with similar *vertex degree* (number of patients). The physician degree distribution is binomial and the average number of patients per physician is n/m . In such a network, agents with the same strategy are statistically indistinguishable.

Then we compare this case with a network where the initial graph is obtained by a non-linear preferential attachment rule, with attachment probabilities $P_i(0) \propto n_i^\gamma$ and different scale exponents γ_D, γ_{ND} for D-physicians and ND-physicians respectively.³ Specifically we consider a variation of scenarios A and C where $\gamma_D = 1$ and $\gamma_{ND} = 0.1$, which make D-physicians more attractive at first, and a variation of scenario B where, at the opposite, $\gamma_D = 0.1$ and $\gamma_{ND} = 1.0$ making ND-physicians more popular. In this way we will test for the effects of heterogeneous popularities within the initial populations of physicians. For these variants of the initial state, we consider the cases of both a pure popularity-driven reallocation and a mixed reallocation, corresponding to choices for the attachment probability as explained at the end of Sect. 2.4. It is worth noting that the initial distribution of patients over physicians corresponds to different, nonlinear scale exponents, in order to make one population more popular than the other at starting time. However, the endogenous dynamics proceeds through linear preferential attachment, corresponding to $\gamma = 1$ for both populations (see Sect. 2.4). In all considered cases, strategy revision is driven by agents' payoffs.

4 Results

4.1 Time Evolution

In a benefit-driven dynamics, patient moves are dictated by the sign of the difference of benefits (1). This difference is positive for all the scenarios, as required by definition of the optimal, non-defensive treatment. Accordingly, patients tend to move from D-physicians to ND-physicians. The strategy revision process of physicians is initially governed by the payoff difference in (2), which is positive for scenarios A and C, and negative for B.

We first analyze the time evolution of a random graph in a benefit-driven case, see Fig. 2. For case A, the ND strategy is favored by the physicians as well as by the patients. D-physicians turn into ND-physicians before going inactive and the D-population eventually becomes extinct. The system converges quite rapidly to a “virtuous” state where all physicians are active and provide the non-defensive treatment.

Case B provides evidence that convergence to the virtuous state cannot be guaranteed in general. Here, patients reach for ND-physicians who, at the very same time, tend to turn into D-physicians. The two effects act antagonistically and, on parity of α , β and β^{ph} , the dynamics is slower and steers the system toward a state where all physicians provide the defensive treatment. Despite being highly litigious at first, the system converges to a state where litigious and non-litigious patients coexist in equal proportions.

For the limit case C, we observe convergence to a virtuous state despite the high intrinsic risk of the non-defensive treatment. However many patients get damaged from highly risky ND treatments and immediately leave. This leads to a fraction of physicians, mostly non-defensive, to become inactive. Given the unfavorable costs and compensations, a slight reduction in the original litigiousness is also observed.

We now repeat previous comparison for the mixed case when reallocation is driven by both benefit and popularity, see Fig. 3, and for the case of a pure popularity-driven reallocation, see Fig. 4. The network at starting time is obtained through nonlinear preferential attachment as discussed in Sect. 3.2.

³ When generating the initial graph by a preferential attachment rule, we do not cap the number of patients. As a consequence, at the very start of the dynamics some physicians may have more than n_{\max} patients, depending on the values of m , n and the scale exponents.

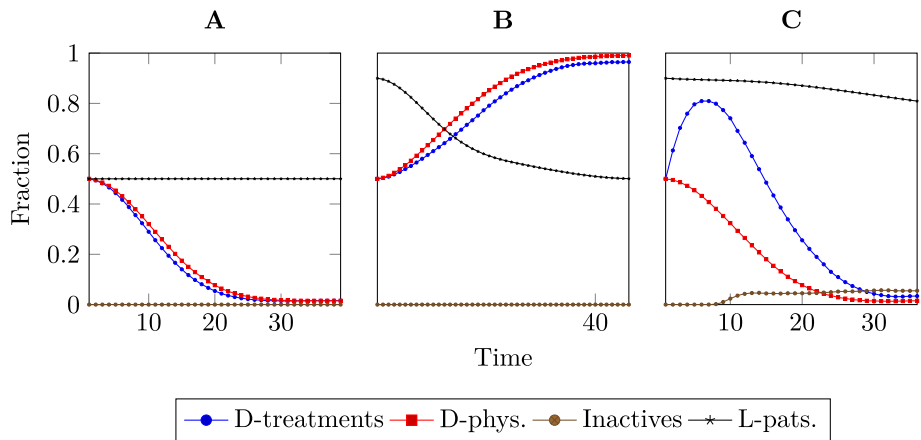


Fig. 2 Time evolution (benefit-driven). Number of patients receiving the defensive treatment, of defensive physicians, of inactive physicians and of litigious patients in a balanced random network when reallocation is driven by an index of average benefit of treatments (Color figure online)

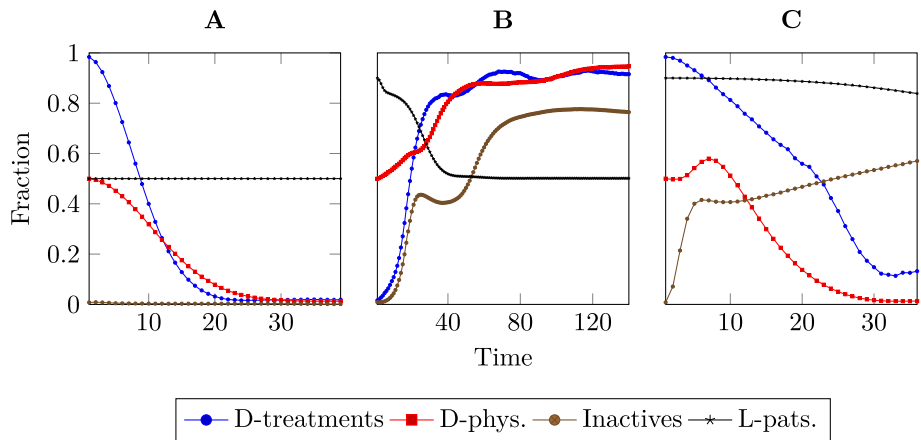


Fig. 3 Time evolution (mixed case). Time evolution of the system when reallocation is determined simultaneously by realized benefit and physician popularity. The initial network features more popular D-physicians in cases A and C, and more popular ND-physicians in case B, and was obtained by means of nonlinear preferential attachment (Color figure online)

We find that neither the initial, highly skewed distribution of the patient strategies nor the popularity-driven attachment can change significantly the long-run behavior observed in the benefit-driven case. The payoff difference between D- and ND-physicians appears determinant for the final state. It is worth noticing that we are intentionally considering cases where the most popular category at the start is the one that is disadvantaged in payoff terms. Correspondingly the speed of convergence to the steady state can be altered significantly, see particularly case B in Fig. 4. Moreover, when physician degree drives reallocation, unpopular physicians are more likely to become inactive even when they provide the optimal treatment. This is evident in scenario C where more than a half of physicians become inactive. We conclude that the dynamics under the study is only slightly affected by the selection criterion used by patients. Even when this choice is entirely determined by popularity and doesn't

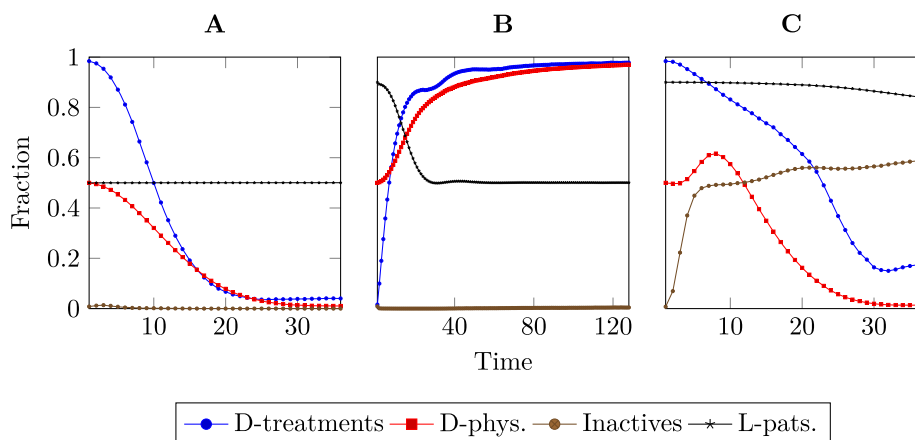


Fig. 4 Time evolution (popularity-driven). Time evolution of the system when reallocation is driven by the degree centrality of physicians. The initial network features more popular D-physicians in cases A and C, and more popular ND-physicians in case B, and was obtained by means of nonlinear preferential attachment (Color figure online)

take into account the benefit of treatments at all, the final state is not altered significantly, as long as we assume that only the damaged patients or those that have experienced many insufficient treatments can move.

4.2 Comparative Statics

For the benefit-driven case, we discuss a sensitivity analysis with respect to changes of selected combinations of parameters, and fixing the others to their values in scenario C. To reduce computational times, the analysis was performed for a smaller network of $m = 40$ physicians and $n = 10^4$ patients, simulating the dynamics over $T = 35$ time steps. The relevant quantities have been computed as Monte Carlo averages over 120 instances.

In Fig. 5, we represent the number of active D-physicians and L-patients with respect to selected pairs of parameters. The plots for n_D highlight that a virtuous system with all physicians providing the optimal treatment emerges for a wide range of parameter values. This holds even though the system is highly litigious ($f_L = 0.9$). However, when the legal system penalizes ND-physicians through high values of p_{ND} or k_{ND} and for given clinical risk, we can expect a prevalence of defensive treatments. Conversely, for given probability of being judged guilty, physicians tend to practice defensive medicine more and more as the clinical risk of the optimal treatment increases. The behavior of n_D as a function of f_L for moderate p_{ND} provides further evidence that a virtuous state can be expected, not only when the probability of cases is small but even in the limit where all patients play a litigious strategy.

Turning to n_L , we first consider the dependence on probabilities (top right panel). In order to be fully understood, such dependence is to be analyzed in the light of the physicians' behavior (left panels) and of the high initial litigiousness. For low to moderate values of q_{ND} the system features a prevalence of virtuous physicians and a reduction in litigiousness is observed. However the system stays litigious in that $n_D/n > 0.5$. This means that for a not too risky optimal treatment, we cannot expect to turn the system into a “neutral” one

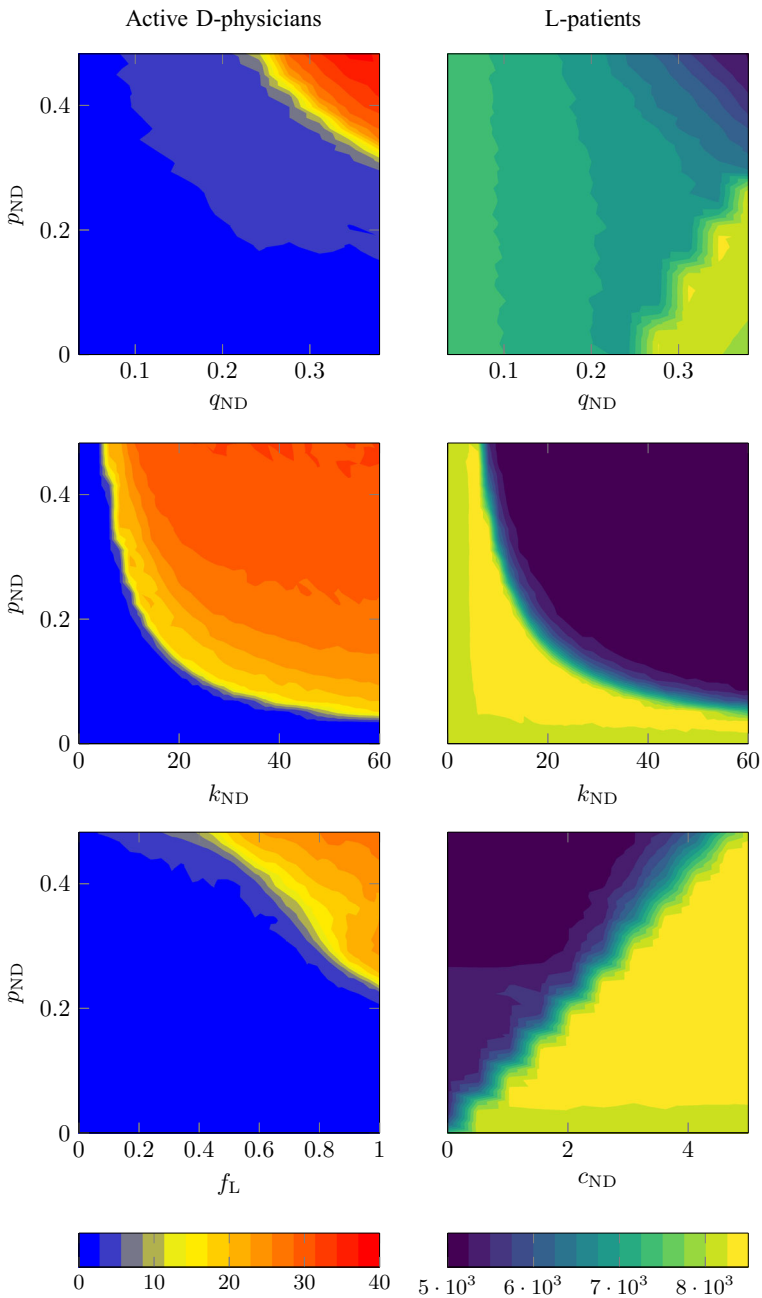
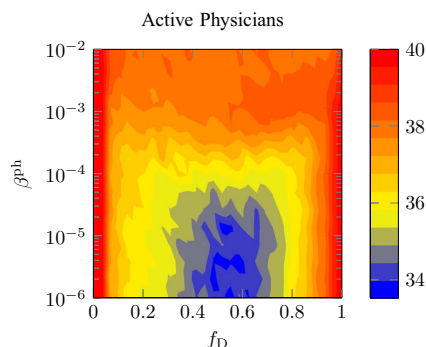


Fig. 5 Sensitivity of the numbers of active D-physicians (left column) and litigious patients (right column) after $T = 35$ time steps. The rest of the parameters have been fixed as in scenario C (Color figure online)

Fig. 6 Effects of physician reactivity on the number of active physicians after $T = 35$ time steps. Unvarying parameters fixed as in scenario C (Color figure online)



with $n_D = 0.5$, even for a favorable court. That is because there still can be a systematic advantage (in patient payoff terms) in being litigious. For a risky treatment with $q_{ND} > 0.25$ and a favorable court, the system stays as nearly as litigious as it was at the beginning, showing that for large q_{ND} the litigious behavior is favored even though defensive medicine is penalized in court. However, increasing p_{ND} has a slightly unintuitive effect as it reduces n_L to roughly one half of the patients (see the blue region in the upper right corner). This can be explained by the fact that a highly unfavorable court steers the system to a state where all physicians are defensive. Since the probability of damage from defensive treatment is low, physicians go to court very rarely and the differential advantage in being litigious goes to zero. This makes indifferent on average to act litigious or not. As a result, we observe convergence to a neutral state with $n_L \approx 0.5$. In other words, for risky treatments we can reduce litigiousness but at the cost of producing a defensive medical system.

The sensitivity of n_L on parameters k_{ND} and c_{ND} also provides valuable insight. For a high cost of litigiousness, increasing p_{ND} increases litigiousness. However, for low to moderate cost, a threshold value of p_{ND} exists separating a litigious and a neutral system neatly. Conversely, for given p_{ND} , decreasing c_{ND} doesn't increase litigiousness as one may expect. On the contrary, when the cost is below a threshold, the system becomes rapidly neutral. A similar behavior is deduced from the heat map of n_L as a function of p_{ND} and k_{ND} . Convergence to a neutral system with $n_L \approx 0.5$ is observed for increasing values of these parameters. Indeed this discourages physicians from providing the optimal treatment and, in the limit of a completely defensive system, patients become effectively strategy-neutral. Since neither a systematic gain nor a penalization would be produced by being litigious, in principle patients may choose randomly which strategy to play from one game to another, which results in equal fractions of litigious and non-litigious patients at the steady state.

In Fig. 6, we show the effect of changing the reactivity β^{ph} of physicians, which dictates how long it takes for them to revise their strategy, on the number of active physicians and for varying f_D . For intermediate f_D and high reactivity, few physicians go inactive as they can catch up with patients' moves and adapt their strategy. At the opposite, for small β^{ph} physicians react slowly and the probability of going inactive before adapting is larger. For a homogeneous system with $f_D \approx 0$ or $f_D \approx 1$, all physicians stay active independently of their reactivity. Indeed, as long as all physicians play the same strategy, they also have the same average performance and payoff. Thus, the probability for a physician to change strategy is small, as is that to systematically outperform another physician and attract their patients.

Finally, Fig. 7 illustrates how the systemic performance index I_p depends on the control parameters. A higher p_{ND} translates into a less performant system: physicians become

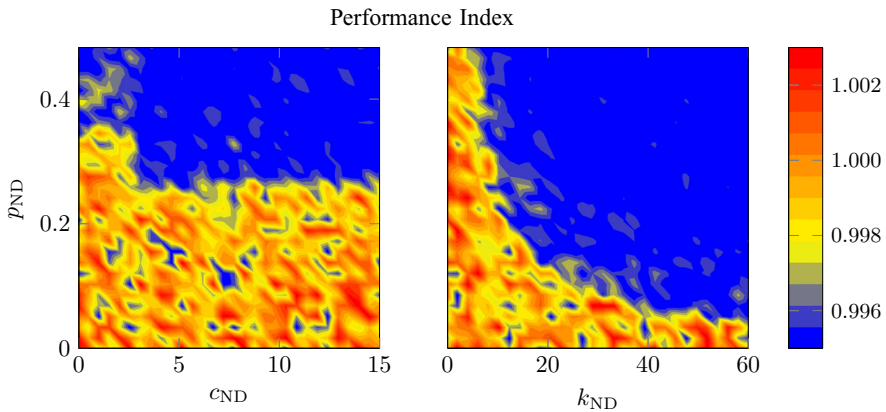


Fig. 7 Systemic performance index after $T = 35$ time steps. Unvarying parameters fixed as in scenario C (Color figure online)

defensive since the probability of being found guilty increases. On the other hand, advisably reducing the compensation for given p_{ND} is effective in producing a virtuous medical system, because a low k_{ND} does not discourage from giving the defensive treatment. We found a reduced sensitivity on c_{ND} . The bluish and yellowish regions roughly correspond to systems where most physicians act defensively and non-defensively, respectively. Since the choice of strategy is driven entirely by the physicians' payoffs, see Eq. (2), and c_{ND} enters them only indirectly via f_L , its effects on I_p are usually of smaller amplitude. The exception is the region of p_{ND} between 0.2 and 0.4, and $c_{ND} \approx 3$. We know from the top-left corner of Fig. 5 that such values of p_{ND} correspond to a transition from a non-defensive to a defensive system. It could be shown that such region is one where the average payoff difference (2) crosses 0. Consequently the role of f_L in determining the sign of the difference is mostly significant. From the bottom-right panel of Fig. 5, we also see that $c_{ND} \approx 3$ approximately represents the boundary that separates a highly litigious system from a neutral one. Correspondingly, being the system neutral when $c_{ND} < 3$, physicians can tolerate even high values of p_{ND} as, on average, their payoff from non-defensive treatments is higher. On the contrary, in the regions far from this boundary, the effects of c_{ND} are small. In general, rising the cost of litigiousness is not guaranteed to be effective in steering the system toward the virtuous state.

5 Conclusions

In this paper, we introduced a stylized dynamical model of a medical system in presence of positive defensive medicine. This was represented in terms of a bipartite network of physicians and patients, where treatments are described as strategic interactions between these agents as a sequence of one-shot games. The network dynamics is twofold. Patients are allowed to change physician, which corresponds to changes in the network topology. Agent strategies change according to their payoffs, while physician choice takes place according to a physician reputation index.

Such model features a rich dynamics that in principle can be altered by regulators changing, in particular, the following control parameters: cost of litigiousness, amount of compensations to damaged patients, and probability for virtuous physicians to be condemned to compensate

a damaged patient. We compared different benchmark scenarios and provided evidence that convergence to a virtuous steady state is not guaranteed. A major result of such comparison is that the steady state does not depend on the litigiousness of the initial system or the initial distribution of strategies in the physician population or the distribution of patients over physicians. Most of all, we showed that the qualitative features exhibited by the model's dynamics are robust with respect to different choices of the reputation, or the criterion patients adopt in selecting a new physician. In particular, reaching a virtuous steady state or an entirely defensive one is something that appears to be independent of the fact that patients look at the quality of treatments directly or they rely merely on popularity to make a choice.

We performed an extensive comparative statics analysis. This was carried out for a scenario that corresponds to a risky optimal treatment only slightly favored in terms of expected benefits, even though it has much higher certain benefit compared to a defensive therapy. This analysis confirmed that a virtuous system is to be expected in a wide region of the parameters space, even for very litigious patients. Only when the legal system is very penalizing toward virtuous physicians we observe a polarization in favor of a defensive strategy. Interestingly this also showed that it is generally difficult to control the litigiousness in the system. Counterintuitively, penalizing litigiousness by increasing legal costs or reducing compensations, or having a court more favorable toward the optimal treatment, are not guaranteed to be effective policies. Indeed, such policies can result in a virtuous system but, in front of a higher probability of cases, a differential advantage can emerge in favor of litigious patients. In terms of agent attributes, our simulations also highlight that a possibly large number of physicians may end up having very few or no patients. This happens when their reactivity is too small and it does not allow them to adapt their strategy as to offset the loss of patients.

Although our results can only give general indications, without necessarily representing empirical results, we believe that the model discussed here and its comparative analysis can be valuable in understanding patient–physician strategic interactions as well as the coupling between the dynamics of agent strategies and that of link formation in the bipartite network. Although the model already exhibits a rich dynamics, an interesting research perspective would be to include heterogeneity in the network by considering, for instance, physicians with varying degree of skillfulness or patients with varying inclination to litigiousness.

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Data Availability The datasets generated during and/or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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References

1. Allard M, Léger PT, Rochaix L (2009) Provider competition in a dynamic setting. *J Econ Manag Strategy* 18(2):457–486
2. Antoci A, Fiori Maccioni A, Russu P (2016) The ecology of defensive medicine and malpractice litigation. *PLoS ONE* 11(3):e0150523
3. Antoci A, Fiori Maccioni A, Russu P (2018) Medical practice and malpractice litigation in an evolutionary context. *J Evol Econ* 28:915–928
4. Antoci A, Galeotti M, Fiori Maccioni A, Russu P (2018) Defensive medicine. Liability insurance and malpractice litigation in an evolutionary model. *Nonlinear Anal Real World Appl* 47:414–435
5. Antoci A, Fiori Maccioni A, Russu P, Sacco PL (2021) Curing is caring? Liability reforms, defensive medicine and malpractice litigation in a post-pandemic world. *Socio-Econ Plan Sci* 80:101164
6. Asher E, Greenberg-Dotan S, Halevy J, Glick S, Reuveni H (2012) Defensive medicine in Israel: a nationwide survey. *PLoS ONE* 2012:e22916140
7. Atlas SJ, Grant RW, Ferris TG, Chang Y (2009) Patient–physician connectedness and quality of primary care. *Ann Intern Med* 150(5):325–335
8. Caldarelli G (2007) Scale-free networks. Complex webs in nature and technology. Oxford University Press, Oxford
9. Casalino LP, Pesko MF, Ryan AM et al (2015) Physician networks and ambulatory care-sensitive admissions. *Med Care* 53(6):534–541
10. Centola D (2020) Physician networks and the complex contagion of clinical treatment. *JAMA Netw Open* 3(1):e1918585
11. Cheng YW, Snowden JM, Handler SJ, Tager IB, Hubbard AE (2014) Litigation in obstetrics: does defensive medicine contribute to increases in cesarean delivery? *J Maternal Fetal Neonatal Med* 27(16):1668–75
12. Chuankai A, O'Malley AJ, Rockmore DN (2018) Referral paths in the US physician network. *Appl Netw Sci* 3:20
13. CTA M (1994) Health care payment systems: cost and quality incentives. *J Econ Manag Strategy* 3(1):93–112
14. Cunningham W, Wilson H (2011) Complaints, shame and defensive medicine. *BMJ Quality Saf* 20(5):449–52
15. Delpini D, Battiston S, Caldarelli G, Riccaboni M (2019) Systemic risk from investment similarities. *PLoS ONE* 14(5):0217141
16. Delpini D, Battiston S, Caldarelli G, Riccaboni M (2020) Portfolio diversification, differentiation and the robustness of holdings networks. *Appl Netw Sci* 5:37
17. Ellis RP (1998) Creaming, skimping and dumping: provider competition on the intensive and extensive margins. *J Health Econ* 17(5):537–555
18. Ellis RP, McGuire TG (1986) Provider behavior under prospective reimbursement: cost sharing and supply. *J Health Econ* 5(2):129–151
19. Feess E (2012) Malpractice liability, technology choice and negative defensive medicine. *Eur J Health Econ* 13:157–167
20. Ford EW, Wells RS, Bailey B (2004) Sustainable network advantages: a game theoretic approach to community based health care coalitions. *Health Care Manage Rev* 29(2):159–169
21. Gal-Or E (1999) Optimal reimbursement and malpractice sharing rules in health care markets. *J Regul Econ* 16(3):237–266
22. Garattini L, Padula A (2019) Defensive medicine in Europe: a ‘full circle’? *Eur J Health Econ* 21:165–170
23. Garattini L, Padula A, Mannucci PM (2020) Defensive medicine: everything and its opposite. *Eur J Intern Med* 74:117–118
24. Glassman PA, Rolph JE, Petersen LP, Bradley MA, Kravitz RL (1996) Physicians' personal malpractice experiences are not related to defensive clinical practices. *J Health Polit Policy Law* 21(2):219–41
25. He AJ (2014) The doctor-patient relationship, defensive medicine and over prescription in Chinese public hospitals: evidence from a cross-sectional survey in Shenzhen city. *Soc Sci Med* 123:64–71
26. Hendee WR, Becker GJ, Borgstede JP, Bosma J, Casarella WJ, Erickson BA, Maynard CD, Thrall JH, Wallner PE (2010) Addressing overutilization in medical imaging 1. *Radiology* 257(1):240–245

27. Hiyama T, Yoshihara M, Tanaka S, Urabe Y, Ikegami Y, Fukuhara T, Chayama K (2006) Defensive medicine practices among gastroenterologists in Japan. *World J Gastroenterol* 12(47):7671–7675
28. Keren-Paz T (2010) Liability regimes, reputation loss, and defensive medicine. *Med Law Rev* 18(3):363–388
29. Kessler D, Mark McClellan M (1996) Do doctors practice defensive medicine? *Q J Econ* 111(2):353–390
30. Klingman D, Localio AR, Sugarman J et al (1996) Measuring defensive medicine using clinical scenario surveys. *J Health Polit Policy Law* 21(2):185–220
31. Landon BE, Keating NL, Barnett ML et al (2012) Variation in patient-sharing networks of physicians across the United States. *JAMA* 308(3):265–273
32. Lien HM, Ma CTA, McGuire TG (2004) Provider-client interactions and quantity of health care use. *J Health Econ* 23(1261):1283
33. Ma CTA, McGuire TG (1997) Optimal health insurance and provider payment. *Am Econ Rev* 685:704
34. Mello MM, Chandra A, Gawande AA, Studdert DM (2010) National costs of the medical liability system. *Health Aff* 29(9):1569–1577
35. Newman MEJ (2010) *Networks: an introduction*. Oxford University Press, Oxford
36. Olbrich A (2008) Heterogeneous physicians, lawsuit costs, and the negligence rule. *Int Rev Law Econ* 28(1):78–88
37. Onnela JP, O'Malley AJ, Keating NL, Landon BE (2018) Comparison of physician networks constructed from thresholded ties versus shared clinical episodes. *Appl Netw Sci* 3:28
38. Pellino IM, Pellino G (2015) Consequences of defensive medicine, second victims, and clinical-judicial syndrome on surgeons' medical practice and on health service. *Updates Surg* 67(4):331–7
39. Quinn R (1998) Medical malpractice insurance: the reputation effect and defensive medicine. *J Risk Insur* 65(3):467–484
40. Ramella S, Mandoliti G, Trodella L, D'Angelillo RM (2015) The first survey on defensive medicine in radiation oncology. *Radiologia Medica* 120(5):421–9
41. Robeznieks A (2005) Wary physicians. *Mod Healthc* 35(23):8–9
42. Rodriguez RM, Anglin D, Hankin A et al (2007) A longitudinal study of emergency medicine residents' malpractice fear and defensive medicine. *Acad Emerg Med* 14(6):569–73
43. Rotter J, Wilson L, Greiner MA, Pollack CE, Dinan M (2019) Shared-patient physician networks and their impact on the uptake of genomic testing in breast cancer. *Breast Cancer Res Treat* 176:445–451
44. Studdert DM, Mello MM, Sage WM, DesRoches CM, Peugh J, Zapert K, Brennan TA (2005) Defensive medicine among high-risk specialist physicians in a volatile malpractice environment. *JAMA J Am Med Assoc* 293(21):2609–2617
45. Zeng Y, Liangwen Z, Guanhuac Y, Fang Y (2018) Analysis of current situation and influencing factor of medical disputes among different levels of medical institutions based on the game theory in Xiamen of China. *Medicine* 97(38):e12501

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