Health Care Manag Sci (2018) 21:119–130
DOI 10.1007/s10729-016-9382-2

A strategic gaming model for health information exchange markets

Diego A. Martinez[1,2] · Felipe Feijoo[2,3,4] · Jose L. Zayas-Castro[5] · Scott Levin[1,2] · Tapas K. Das[5]

Received: 15 February 2016 / Accepted: 29 August 2016 / Published online: 6 September 2016
© Springer Science+Business Media New York 2016

Abstract Current market conditions create incentives for some providers to exercise control over patient data in ways that unreasonably limit its availability and use. Here we develop a game theoretic model for estimating the willingness of healthcare organizations to join a health information exchange (HIE) network and demonstrate its use in HIE policy design. We formulated the model as a bi-level integer program. A quasi-Newton method is proposed to obtain a strategy Nash equilibrium. We applied our modeling and solution technique to 1,093,177 encounters for exchanging information over a 7.5-year period in 9 hospitals located within a three-county region in Florida. Under a set of assumptions, we found that a proposed federal penalty of up to $2,000,000 has a higher impact on increasing HIE adoption than current federal monetary incentives. Medium-sized hospitals were more reticent to adopt HIE than large-sized hospitals. In the presence of collusion among multiple hospitals to not adopt HIE, neither federal incentives nor proposed penalties increase hospitals' willingness to adopt. Hospitals' apathy toward HIE adoption may threaten the value of inter-connectivity even with federal incentives in place. Competition among hospitals, coupled with volume-based payment systems, creates no incentives for smaller hospitals to exchange data with competitors. Medium-sized hospitals need targeted actions (e.g., outside technological assistance, group purchasing arrangements) to mitigate market incentives to not adopt HIE. Strategic game theoretic models help to clarify HIE adoption decisions under market conditions at play in an extremely complex technology environment.

Keywords Health information exchange · Medical record linkage · Game theory · Market models

Electronic supplementary material The online version of this article (doi:10.1007/s10729-016-9382-2) contains supplementary material, which is available to authorized users.

✉ Diego A. Martinez
dmart101@jhmi.edu

[1] Department of Emergency Medicine, Johns Hopkins University, Baltimore, Maryland, USA

[2] Systems Institute, Johns Hopkins University, Baltimore, Maryland, USA

[3] Engineering Sciences Department, Universidad Andres Bello, Santiago, Chile

[4] Department of Civil Engineering, Johns Hopkins University, Baltimore, Maryland, USA

[5] Department of Industrial and Management Systems Engineering, University of South Florida, Tampa, Florida, USA

1 Background and Significance

A 10-year expectation for healthcare organizations in the United States is coordinated exchange of electronic patient data through far-reaching health information exchange (HIE) networks. [1, 2] The federal government has taken an active role to stimulate electronic medical record (EMR) interconnectivity. Enacted in 2009, the Health Information Technology for Economic and Clinical Health (HITECH) Act has provided a $2,000,000 base incentive for those hospitals electronically exchanging patient information with unaffiliated providers. This includes other *unaffiliated* hospitals and ambulatory care facilities that are regional and sometimes in direct competition. Although recent evidence shows mixed effects of HIE, two recent systematic reviews suggest it may be due to a lack of widespread HIE adoption. [3, 4] There has been an uptick in HIE adoption since the enactment of the HITECH Act; however, only 40 % of hospitals and 14 % of solo practices are conducting HIE activities with significant state-to-state variations. [5, 6] Common barriers to HIE adoption include financial impediments to investment, interface and workflow issues, privacy and security regulations, and strategic concerns regarding the competitive advantage of “owning” patients’ data. [7–12].

A recent report to Congress highlights that current HIE market conditions create incentives for some entities to exercise control over patient data in ways that unreasonably limit its availability and use. [13] This issue, named *health information blocking*, is used to maintain a captive market share and reinforce market dominance. Current evidence shows that hospitals being for-profit, hospitals controlling major regional market shares, and hospitals in more concentrated markets are at decreased likelihood of adopting HIE. [14, 15] Large health systems (e.g., accountable care organizations) are motivated to exchange electronic patient data internally, maintaining a common medical record, but are less likely to exchange with competitors and unaffiliated providers. [16] Although providers are legally required to share patients’ records, there is anecdotal evidence that significant barriers exist to exchange and some providers are hesitant to release records to patients transferring to other providers. [13, 17–21] While the evidence is limited, there is little doubt that health information blocking is occurring and obstructing nationwide HIE. [13]

Various modeling studies have been undertaken to study HIE network structures and inform policy. [22–28] However, only a few have focused on issues related to health information blocking and the strategic hospital decision to share patient records with competitors. Zhu and colleagues proposed a game theoretic approach to studying the strategic behavior of data owners. [29] Desai developed a game theoretical model to analyze the potential loss of competitive advantage due to HIE adoption. [30] A crucial difference between these studies is the type of interaction assumed between hospitals and patients, and among competing hospitals. In hospital competition focused models, hospital interactions can be summarized in terms of conjectural variation (i.e., each hospital’s decision to adopt HIE is predicated on the way it perceives its competitors may react). Our proposed model, unlike previous approaches, considers patients’ options of where to seek healthcare services by calculating oligopolistic equilibriums of HIE adoption decisions using hospital utility function conjectural variations. The resulting bi-level mathematical program can be used to deepen our understanding of health information blocking under different market structures.

2 Objective

Our objective is to describe a mathematical model for estimating the willingness of a set of healthcare organizations to adopt HIE, which considers different levels of federal incentives and health information blocking. Given outlined assumptions, the model illuminates optimal levels of financial incentives and the effects of information blocking across a 9-hospital region in Florida.

3 Material and Methods

We used changes in the expected number of hospital visits (i.e., market share) as the primary measure that drives likelihood of a hospital to adopt HIE. In our models, hospitals seek to maximize their profit and patients seek to maximize their utility. The hospital profit is a function of the number of patients they see, the costs of adopting HIE, the marginal benefits of adopting HIE (e.g., reduction of repeated testing), and the federal incentives for adopting or not adopting HIE. The patient utility is a function of their personal preference, the quality of care offered by the hospital, and the costs of switching provider. Each hospital profit is constrained to a pre-determined budget for HIE investment, and each patient utility function is constrained to only the hospitals able to provide services the specific patient needs. Although we assume all patients are insured, their movement from one provider to another is constrained by their healthcare needs. Hospitals are incentivized to adopt HIE to minimize hospital readmissions, decrease unnecessary duplicate testing, attract patients from other hospitals (i.e., increase market share), and collect the federal financial incentives for adopting HIE technology. Hospitals are dis-incentivized to adopt HIE as a way to reduce patient migration. Patients may be willing to switch providers due to personal preferences (e.g., minimize traveling distance to provider, word of mouth recommendation) or the quality of care provided at each hospital (e.g., hospital ranking). Patient switching providers is facilitated by HIE because transmission of electronic medical records is enabled compared to paper-based transactions (i.e., faxes) which are cumbersome. [31] To simulate the effect of federal incentives, we evaluated the impact of a \$2,000,000 incentive for hospitals adopting HIE and a \$2,000,000 penalty for hospitals not adopting HIE. To simulate the effect of health information blocking, we artificially force a subset of hospitals to not adopt HIE, and then assessed the impact of these artificial collusions on other hospitals and their willingness to adopt HIE.

The data set included hospital admissions during a 7.5-year period to a hospital network in adjacent counties and other information about provider organizations such as number of beds (for characteristics of the hospitals see section 4.1). The average price of healthcare services at each hospital and the HIE adoption costs were collected from published literature. Other model parameters including the costs a patient incurs when switching providers, the marginal benefits a patient receives when receiving healthcare services at a hospital, and the hospital budget designated for HIE adoption were randomly generated in ranges of plausible values. In the absence of data, patients' personal preferences for a particular hospital were assume to have a high variability, and thereby we used a uniform distribution to simulate numerical values. We describe next the market details, the mathematical representation of the market, and the proposed solution strategy to find the market equilibrium.

3.1 Market description

We consider a finite number of hospitals serving a finite number of patients. Hospitals decide whether or not to adopt HIE based on two sources of economic value: *inherent value* and *network value*. Inherent value is the value a hospital derives from the adoption of HIE (e.g., reduction of readmissions or duplicated testing) and network value is the value a hospital derives from other hospitals' use of HIE (e.g., patients migrating from other hospitals). By not adopting HIE, hospitals may be able to increase their profits by reducing patient migration. Alternatively, by adopting HIE, hospitals may increase profits by treating patients migrating from other hospitals and by receiving inherent value of adopting HIE (e.g., reduction of readmissions or duplicated testing). In a community served by a multi-hospital system, a Nash equilibrium will occur when no hospital has any incentive to change unilaterally its HIE adoption decision. On the other hand, patients decide whether or not to switch the hospital where they receive healthcare services based upon an extension of the utility function used in [30]. The model presented in [30] is similar to ours, except for two fundamental differences. The first difference is that in [30] a duopoly market is assumed—the multi-hospital equilibriums are not calculated nor discussed. We instead consider reactions of more than two competing hospitals in a given community, which we argue is a more realistic representation of the HIE marketplace. Second, our model is constrained by hospital HIE adoption budgets and by patient allocation needs, i.e., patients in our model have specific care needs that cannot be served by every hospital.

3.2 Model assumptions

All hospitals maximize expected payoffs and have a designated budget for HIE adoption. Patients maximize expected utilities, which are measured in terms of the quality of care offered by each hospital, their personal preferences, and the switching costs generated at the time of moving health information from one hospital to another one. We assume all patients have medical insurance, and thereby they are insensitive to price changes on healthcare services. [32] We use administrative data to calculate the average number of inpatient encounters to each of the hospitals under study, and then we calibrate the model parameters (i.e., vertical quality component offered by each hospital, v_i) until divergences with historical patient volumes are below 5 %. The timing of the model is as follows. First, patients are randomly assigned to an index hospital with imperfect information about their personal preference. Second, patients learn their hospital preference perfectly, and we assume the prospect of the hospital adopting HIE causes no impact on the patient's utility function. Third, hospitals make a binary decision whether or not to adopt HIE. Finally, patients decide whether or not to switch the index hospital. If the index hospital decides to adopt HIE, then the patient switching costs are reduced to zero (patient switching costs are reduced to zero even if only the index hospital decides to adopt HIE).

3.3 Model formulation

Mathematically, the HIE market can be formulated as an oligopolistic market equilibrium model on a network consisting of the node sets I and J, where the set I corresponds to the hospitals in a given community and the set J corresponds to the patients served by the multi-hospital network. Each hospital takes as inputs its perceived market conditions (including any competitors' service and demand functions) and maximizes profit under a set of equilibrium constraints. The upper-level variables consist of the hospital's decision to adopt HIE, and the lower-level is the patient's decision as to switch hospital. The upper-level problem is parameterized by the patient's willingness to switch which is restricted by given bounds; such bounds constitute the upper-level constraints. The upper-level objective is the hospital's profit, equal to its revenues less its costs. A single-hospital problem focuses on a hospital denoted by $i^* \in I$. The following is the notation used in the formulation of this problem Table 1

The lower-level patient switching problem is formally stated as the following mathematical program in variable t_{ij} and y_{ij}, parametrized by decision e_i for $i \in I$.

- Maximization of patient's utility: each patient decides where to consume healthcare services (t_{ij}) based on the quality of care offered by each hospital (v_i), personal preference (r_{ij}), and the costs of switching provider (s). The costs of switching provider is reduced to zero if the hospital decides to adopt HIE. The factor (α) allows to convert the patient's preferences to monetary values.

$$\max_{t_{ij},y_{ij}\in\{0,1\}^2} \sum_i \sum_j t_{ij}\left[\alpha\left(v_i + r_{ij}\right) - (1-e_i)s\right] \tag{1}$$

- constrained by the set of hospitals to which a patient cannot migrate due to special healthcare needs, i.e., patients in

Table 1 Model notation

Symbol	Definition
	Sets:
I	Set of all hospitals in the community
J	Set of all patients in the community
T_j	Set of all hospitals where patient j cannot purchase healthcare services, $T_j \subset I$
	Indices:
i	Hospital in the community
j	Patient in the community
	Parameters:
α	Marginal product of the patient's input
v_i	Vertical quality component offered by hospital i
r_{ij}	Personal preference component for hospital i by patient j
s	Switching cost
p	Price of service
q_i	Number of patients served by hospital i
f_i	Quantity of federal monetary incentive for adopting HIE
β_i	Inherent value per patient a hospital i receives for adopting HIE
C_{HIE}	Fixed HIE adoption cost
B_i	Budget allocated by hospital i for HIE adoption
	Lower-level patient decision variables:
t_{ij}	1 if patient j consumes from hospital i and 0 otherwise
y_{ij}	1 if patient j migrates from hospital i and 0 otherwise
	Upper-level hospital decision variables:
e_i	1 if hospital i adopts HIE and 0 otherwise

need of tertiary care versus secondary or primary care: for all patients $j \in J$,

$$\sum_{i \in T_j} t_{ij} = 0 \tag{2}$$

- by the migration of a patient to a unique hospital to avoid having patients visiting two providers at the same time: for all patients $j \in J$,

$$\sum_{i \neq i^*} t_{ij} = y_{i^* j} \tag{3}$$

- and, by the binary decision variables

$$t_{ij}, y_{ij} \in \{0, 1\}^2 \tag{4}$$

With the lower-level problem defined, we may now complete the upper-level problem that hospital $i^* \in I$ solves to determine its decision of adopting HIE. Specifically, taking t_{ij} and y_{ij} for all $j \in J$ as given, hospital $i^* \in I$ maximizes its profit.

- Maximization of hospital's profit: each hospital decides whether or not to adopt HIE (e_i) based on the number of patients they serve (q_i), the number of patients migrating from other hospitals (t_{ij}), and the number of patient leaving the hospital (y_{ij}). Also, the hospital takes into account the marginal benefits of adopting HIE (β_i), the cost of adopting HIE (C_{HIE}), and the federal incentives/penalties associated with HIE adoption (f_i).

$$\max_{e_i \in \{0,1\}} p\left[q_{i^*} + \sum_j t_{i^* j} - \sum_j y_{i^* j}\right] + e_i\left[\beta_i\left(q_{i^*} + \sum_j t_{i^* j} - \sum_j y_{i^* j}\right) - C_{HIE} + f_i\right] \tag{5}$$

- constrained by the budget that each hospital allocates for HIE adoption: for all hospitals $i \in I$,

$$e_i[C_{HIE} - f_i] \leq B_i \tag{6}$$

- and by the binary decision variables

$$e_i \in \{0, 1\} \tag{7}$$

Rewriting the resulting formulation (1) – (7), we obtain the following bi-level integer program, to which we refer as BiIP. The upper-level of problem (8) represents the interest of hospital $i \in I$, while the lower-level represents the interest of patient $j \in J$. The hospital is classified as leader of the bi-level program, and the patients are classified as followers (leader-follower or Stackelberg game). Patients in our model can arguably switch providers more easily than may be the actual case in other regions due to, for example, the narrowness of networks. There are multiple factors influencing the patient health insurance purchase decision that, for the sake of simplicity, were compounded in a single factor, r_{ij}. However, if a greater level of complexity about patient's preferences is to be accommodated, additional parameters within the current model structure will need to be added to account for specific patient's preference and their type of insurance coverage.

BiIP:

$$\max_{e_i\in\{0,1\}} p\left[q_{i^*}+\sum_j t_{i^*j}-\sum_j y_{i^*j}\right]+e_i\left[\beta_i\left(q_{i^*}+\sum_j t_{i^*j}-\sum_j y_{i^*j}\right)-C_{HIE}+f_i\right]$$
$$\text{subject } to\ e_i[C_{HIE}-f_i]\le B_i, \forall i, e_i\in\{0,1\},$$
$$\left(t_{i^*j}, y_{i^*j}\right)\in \max_{t_{ij},y_{ij}\in\{0,1\}^2}\left\{\begin{array}{c}\sum_i\sum_j t_{ij}\left[\alpha\left(v_i+r_{ij}\right)-(1-e_i)s\right]:\\ \sum_{i\in T_j} t_{ij}=0, \forall j, \sum_{i\neq i^*} t_{ij}=y_{i^*j}, \forall j,\\ t_{ij}, y_{ij}\in\{0,1\}^2\end{array}\right\}. \tag{8}$$

3.4 Solution strategy for the single and multi-hospital problem

Bi-level optimization models have been widely used to study strategic behavior of market participants in different markets. [33–35] Bi-level models include two mathematical programs, where one serves as a constraint on the other. For a lower level model, with convex and feasible space and objective function, the first order necessary conditions represent a solution for the model. [36] The model presented in (8) does not comply with these assumptions since the lower-level model is a non-convex model due to the presence of integer decision variables. A number of solution approaches have been discussed to tackle problems of this type. However, most of these approaches do not necessarily guarantee a solution to be optimal, [37] and if they do, computational requirements are cost prohibitive for large problems as the one under study. [38].

To guarantee that an optimal solution is obtained for the formulation presented in (8), the bi-level model is solved in two steps. First, we fixed the hospital's decision of whether to adopt ($e_i = 1$) or to not adopt ($e_i = 0$) HIE. Second, given the fixed hospital's decision, the lower level model becomes a single level mixed integer problem that can be solved independently. Third, once the lower level model is solved for each possible value of e_i, we obtain the optimal solution for hospital $i \in I$. The optimal solution is the maximum between $F(e_i = 1)$ and $F(e_i = 0)$, where $F(e_i)$ represents the profits of hospital $i \in I$.

When multiple hospitals participate in the HIE market, the equilibrium strategies among those hospitals need to be obtained. In this context, each hospital solves their bi-level model. Since the bi-level solution approach considers testing each possible hospital strategy, the corresponding market equilibrium can be formulated as a matrix game. Each position in the matrix game represents the profit of each hospital for a unique combination of strategies $E(e_1, e_2, e_3, \ldots, e_i)$. The representation of the matrix game and solution approach for obtaining the market equilibrium is presented in Fig. 1.

As stated earlier, each position in the matrix game represents a combination of strategies $E(e_1, e_2, e_3, \ldots, e_i)$ of the hospitals. In order to obtain an equilibrium, we evaluate each combination of these strategies in the lower-level problem and calculate the profit for each hospital according to the hospital's objective function described in (5). Once each possible strategy combination in the matrix is populated with the corresponding hospitals' profits, the equilibrium can be obtained. A strategy profile $E^*\left(e_1^*, e_2^*, e_3^*, \ldots, e_i^*\right)$ is a Nash equilibrium

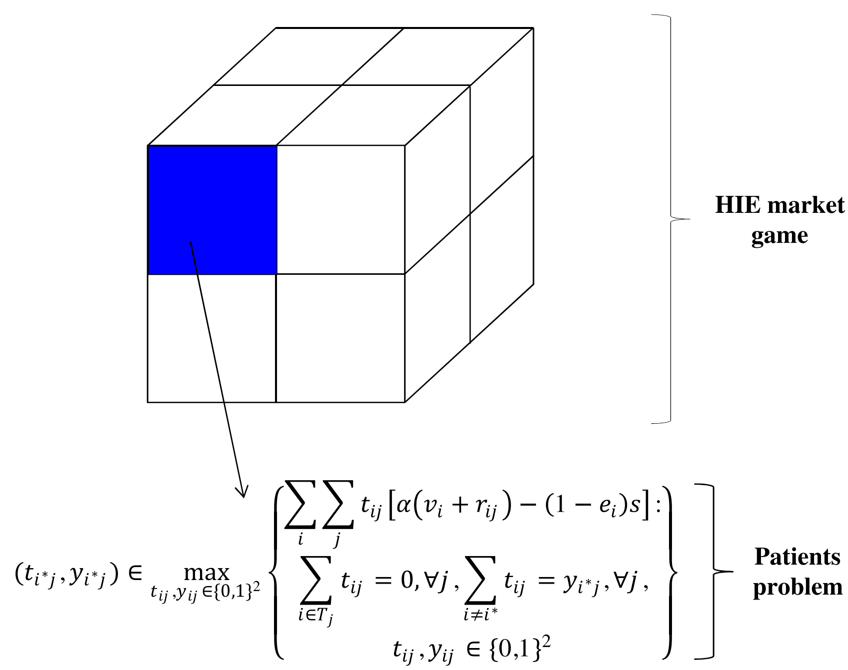

Fig. 1 Diagram of the solution approach for obtaining market equilibrium in a multi-hospital problem. Abbreviations: HIE, health information exchange

(NE) if no unilateral deviation in strategy by any single player is profitable for that player. That is, the strategy E^* $(e_1^*, e_2^*, e_3^*, ..e_i^*)$ is said to be a NE if:

$$\forall i \in I,\ F_i\left(e_i^*, e_{-i}^*\right) \geq F_i\left(e_i, e_{-i}^*\right) \quad (9)$$

If a pure NE cannot be found, a mixed strategy NE (MSNE) can be always found as proven by [39]. An MSNE assigns a probability distribution to the set of strategies that hospitals can take. The probability distribution is understood in our context as the willingness of hospitals to adopt HIE.

3.5 Numerical experiments

We conduct several numerical studies to answer the following fundamental questions: How will HIE adoption rates be affected by federal incentives? How will HIE adoption be affected by health information blocking? To respond the first question, we expose each hospital in the model to current federal monetary incentives of up to \$2,000,000, if they adopt HIE; and to a set of proposed penalties of up to \$2,000,000, if they do not adopt HIE. To answer the second question, we simulate health information blocking by randomly forcing a set of hospitals to not adopt HIE, and then we assess the impact of such decision in the other hospitals' willingness to adopt HIE—network effects. Additional sensitivity analyses were performed to determine how different costs structure will impact the willingness of hospitals to adopt HIE (see Supplementary Material 2). We examine the results of these experiments from two distinct perspectives: 1) the total number of hospitals that are willing to adopt HIE in the region, and 2) the expected number of patients in the community that will be potentially counted in the HIE network. We estimate the expected number of patients in HIE by multiplying the willingness of each hospital to adopt HIE by their respective patient volume. For example, if two hospitals have 60 % and 20 % willingness to adopt HIE, respectively; and their average patient volume are 1000 and 500 patients per year, respectively; then the expected number of patients in the HIE network are 700 (0.6·1000 + 0.2·500 = 700).

4 Results

The novel integration of mathematical programming and game theory enabled us to estimate the willingness to adopt HIE in a given community under (1) various scenarios of federal monetary incentives, and (2) different levels of health information blocking (i.e., hospital collusions to not adopt HIE). The utility of this model in HIE policy development is illustrated through analysis of an HIE marketplace across a 9-hospital region in Florida.

4.1 Sample hospital network and model validation

Patient volume data were collected from administrative claims of nine hospitals geographically located within three adjacent counties in Tampa, Florida. Hospitals with 88–218 beds were classified as *medium-sized* and those with more than 218 beds as *large-sized*. The dataset includes 1,093,177 encounters from January 2005 to July 2012. The marginal product of the patient's input, α, is set to \$150. The switching cost, s, is set to \$50. The average price of service for each patient encounter, p , is set to \$9700 as presented in [40]. To be conservative, the inherent value per patient a hospital i receives from HIE are set to 60–70 % of the values presented in [41] of \$26 per hospital admission. The federal monetary incentives, f_i, are set to \$2,000,000. [42] Since evidence on the costs of HIE adoption is scarce, we set HIE adoption cost, C_{HIE}, at \$900,000 based on anecdotal evidence [43]. The HIE adoption budget for each hospital i was randomly generated between [\$800,000, \$1,000,000] (see Table 2). The patients' personal preferences, r_{ij}, were randomly generated in the interval (0, 1] (see Supplementary Material 1). The vertical quality component of each hospital, v_i, can take any values in the interval (0,1], and it was used to calibrate the model until divergences from the actual average patient volume per year were less than 5 % (see Table 2).

The BiIP model was implemented in GAMS and solved using CPLEX. [44] The multi-hospital MSNE search was performed using the algorithm presented in [45] and implemented in MATLAB. [46] The MSNE search method is performed by reformulating the NE search into an optimization problem that is solved via quasi-Newton method.

4.2 Influence of Federal Monetary Incentives on promoting HIE adoption

To investigate the impact of federal incentives on HIE adoption, we calculated multi-hospital MSNE under scenarios of penalties of up to \$2,000,000 for those hospitals not adopting HIE and incentives of up to \$2,000,000 for those hospitals adopting HIE. As presented in Fig. 3, we found higher sensitivity to penalties than incentives. We also found that not always a greater incentive (or penalty) is the most effective strategy to promote HIE adoption in a given community. For example, our results suggest that a penalty of \$500,000 is more effective than a penalty of \$1000,000 to generate significant engagement of the hospitals in the community under study. Specifically, with no federal incentives (\$0): self-interested behavior by all hospitals causes them–at equilibrium–to balance perfectly between adopting or not adopting HIE. Larger hospitals have a higher likelihood of HIE adoption, because they have the incentives of both capturing HIE inherent value and gaining market due to patient migration from smaller hospitals. But with only a small change to the

Table 2 Model parameters and calibration results. Medium-sized hospital, 88–218 beds; large-sized hospital, >218 beds

	Hospital 1	Hospital 2	Hospital 3	Hospital 4	Hospital 5	Hospital 6	Hospital 7	Hospital 8	Hospital 9
Size	Large	Medium	Large	Medium	Large	Medium	Medium	Large	Medium
Actual average patient volume per year [admissions]	4013	2162	7830	1205	3425	1759	2358	7813	1106
r_{ij} mean (median, IQR range)	0.4999 (0.5004, 0.2491–0.748)	0.5045 (0.5056, 0.254–0.7581)	0.4988 (0.4987, 0.245–0.7498)	0.5003 (0.5004, 0.2486–0.7513)	0.5001 (0.5008, 0.2488–0.749)	0.5016 (0.5034, 0.2519–0.751)	0.5002 (0.5028, 0.2517–0.7459)	0.5 (0.5005, 0.2521–0.7486)	0.5006 (0.5015, 0.2491–0.7499)
β_i [$]	15.36	16.5	13.86	16.47	19.72	13.2	16.12	15.18	16.47
B_i [$]	882,107	846,300	796,943	731,111	796,010	856,995	852,583	840,047	863,011
Simulated average patient volume per year [patients]	4072	2221	8203	1230	3528	1782	2465	8063	1107
Calibration error [admissions (%)]	59 (1.5)	59 (2.7)	373 (4.8)	25 (2.1)	103 (3.0)	23 (1.3)	107 (4.5)	250 (3.2)	1 (0.1)

federal incentives, market equilibriums can dramatically shift. The change is as follows: suppose the government decides to increase the federal incentives from $0 to $500,000 to motivate HIE adoption. Shouldn't each hospital's likelihood of adoption increase? The model demonstrated a new market equilibrium in this new HIE that leads to increasing likelihood of HIE adoption for only medium-sized hospitals. In Fig. 2 at $500,000 of federal incentives, every large hospital risks market share losses due to patient migration to those medium-sized hospitals that are now willing to adopt HIE. As a result, we see larger hospitals reducing their likelihood of adoption while medium-sized hospital increasing their likelihood of adoption. This phenomena–that adding more resources to a network can sometimes hurt performance at equilibrium–was first articulated by Dietrich Braess in 1968, [47] and it has become known as Braess' Paradox. Like many counterintuitive paradigms, the right combination of conditions must coalesce to trigger. Similar phenomenon has been has been observed empirically in transportation networks. [48].

Under a particular set of assumptions, hospitals may set HIE adoption decisions to threaten the value of HIE even with federal monetary incentives in place. Figure 2 also shows that federal penalties have a strong stability property. If slightly more than a given penalty is used, the likelihood of HIE adoption gets pushed to 100 %. If slightly less than a given federal penalty is used, then the likelihood of HIE adoption gets pushed to 100 %. So in the event of a 'near miss' in the proposed federal penalty structure, we would expect the outcome to settle down to 100 % HIE participation in the region under study. The situation looks different–and highly unstable–in the vicinity of the equilibriums under federal incentives. If slightly more than a proposed federal incentive is used, then either a downward or upward pressure drives the likelihood of HIE participation away from the initial equilibrium. Specifically, if exactly $1,000,000 of federal incentives are offered for adopting HIE, then we are at equilibrium with high likelihood of HIE participation across all hospitals. But if the incentive is even slightly off from $1,000,000, the system will tend to spiral up or spiral down to a significantly. Thus, particular levels of federal incentives are not just unstable equilibriums; they may represent critical points or tipping points, in the success of HIE adoption in a given region.

4.3 Influence of Federal Monetary Incentives on promoting HIE adoption in a community suffering health information blocking

To examine the impact of health information blocking on HIE adoption, we calculated multi-hospital equilibriums under scenarios of collusions among a subset of hospitals to not adopt HIE, and then assessed the impact of these collusions on others willingness to adopt HIE (i.e., network effect analysis). To imitate the current policy environment, we set federal

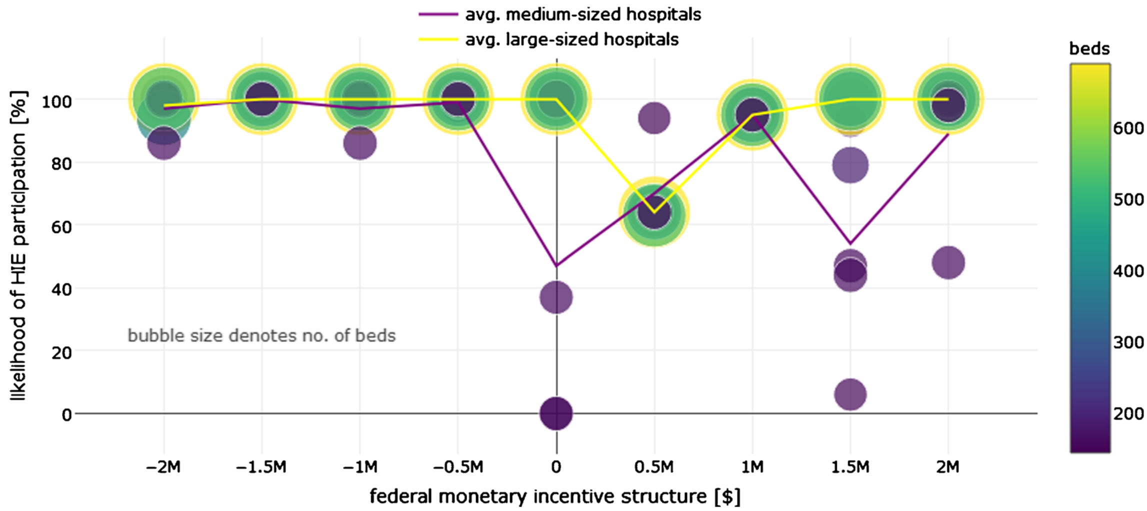

Fig. 2 Correlation between federal incentive structure, likelihood of HIE adoption and hospital size (number of beds). Abbreviations: HIE, health information exchange

incentives at $2,000,000 for hospitals adopting HIE. As presented in Fig. 3, we found that deliberate collusions to not adopt HIE diminish the effectiveness of current federal incentive structures. Although health information blocking complaints are frequently attributed to health IT developers, we found that provider-initiated health information blocking may also become a significant barrier for nationwide EMR interconnectivity even with federal monetary incentives in place. As presented in Fig. 3a, when simulating 1-hospital collusions, we found that hospitals 1, 3 and 6 have significant

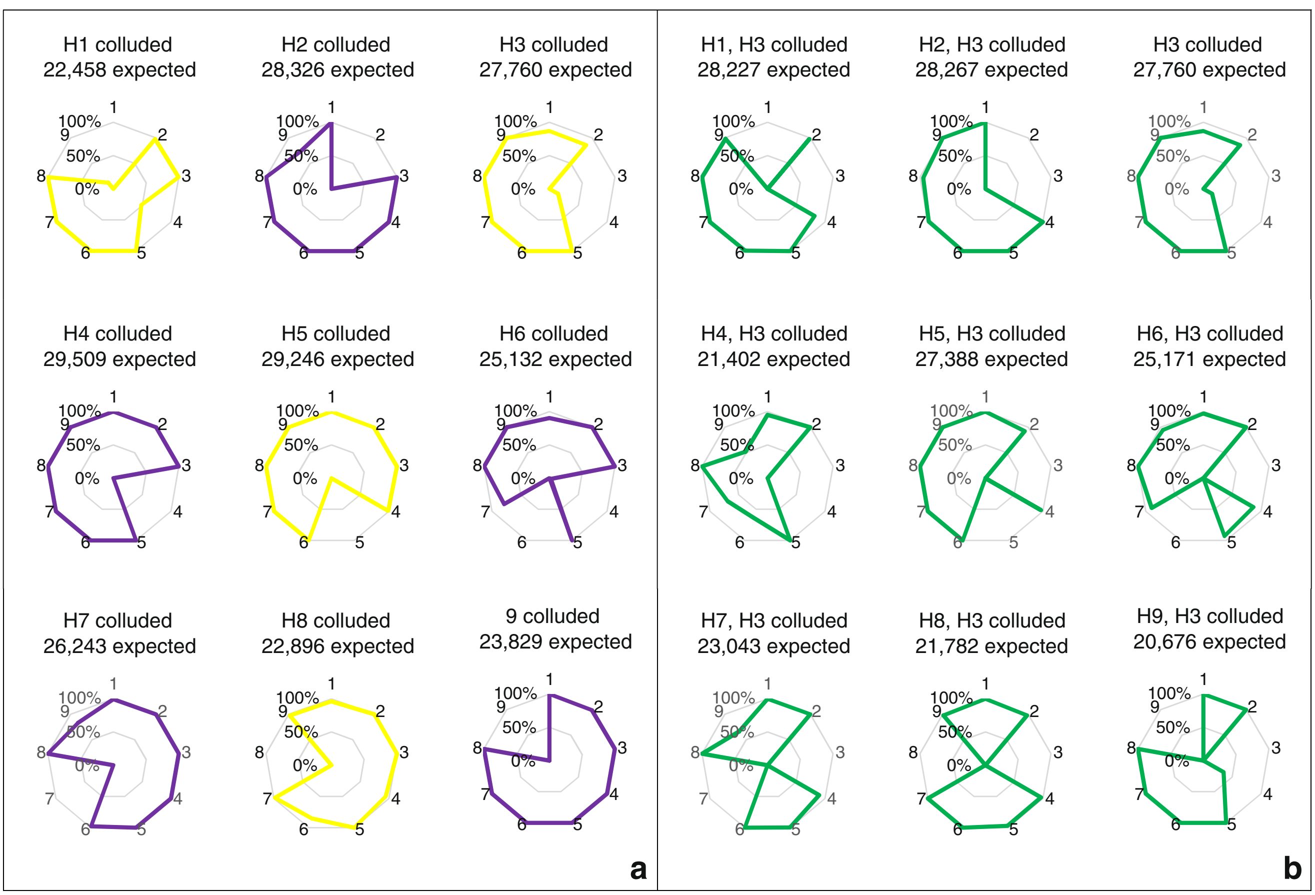

Fig. 3 Influence of federal monetary incentive of $2,000,000 in a community with 1-hospital collusion (Fig. 3a) and 2-hospital collusion to not join HIE (Fig. 3b)

influence over hospital 4's HIE adoption decision. Hospital 4 is a medium-sized hospital with low quality component (v_i=0.68) and low budget for HIE adoption (β_i=\$731,111). In terms of expected number of patients in the HIE network, we found that hospital 1 health information blocking is the most significant, because it reduces the expected number of patients in HIE by 29 % from 31,671 to 22,458 (31,671 is the total number of patients seeking for healthcare services in our models). Hospital 1 not only affects interconnectivity efforts by not allowing its patients to keep their medical records in the network, but also by influencing other hospitals HIE adoption decisions, and thereby impacting the other hospital patients as well. Hospital 1 is a large-sized hospital with low quality component (v_i=0.810) and high budget for HIE adoption (β_i=\$882,107) relative to other large-sized hospitals. As presented in Fig. 3b, when analyzing 2-hospital collusions, we found that hospitals 3 and 7 have a significant effect on hospital 4 and 9. Hospital 4 is a medium-sized hospital with a low quality component (v_i=0.680) and low budget for HIE adoption (β_i=\$731,111) relative to other large-sized hospitals, and hospital 9 is a medium-sized hospital with low quality component (v_i=0.675) and high budget for HIE adoption (β_i=\$863,011) relative to other medium-sized hospitals. In terms of expected patients in the HIE network, we found the collusion between hospitals 3 and 9 to not adopt HIE is the most significant, because it reduces the expected number of patients in HIE by 35 % from 31,671 to 20,676. This collusion reduced the incentives for hospital 4 to adopt HIE, whilst all the others remain eager to adopt. Hospital 3 is a large-sized hospital with a high quality component (v_i=0.680) and low budget for HIE adoption (β_i=\$796,943) relative to other large-sized hospitals, and hospital 9 is a medium-sized hospital with low quality component (v_i=0.675) and high budget for HIE adoption (β_i=\$863,011) relative to other medium-sized hospitals. To determine how different HIE adoption cost structures impact the willingness of medium- and large-sized to invest on HIE, we performed a sensitivity analysis on C_{HIE}. As expected, the higher the cost for medium-sized hospitals to adopt HIE, the less willingness of all hospitals to join the HIE network (see Supplementary Material 2 for more details on the sensitivity analysis).

In summary, results suggest that health information blocking produces local network effects, in which each hospital is influenced by the decisions made by a subset of other hospitals in the region. Our results also suggest that federal incentives of \$2,000,000 were not able to mitigate these negative network effects, and hospitals with low quality component are at the higher risk of not adopting HIE because of the risk of losing market share. Health information blocking becomes even more important when evaluated from the perspective of how many patients in the community will be potentially counted in the HIE network. Small collusions among one or two hospitals reduced the expected number of patients in HIE by at least 29 %.

5 Discussion

The intent of the HITECH Act was to drive the rapid adoption of interoperable EMR systems to support coordinated care and improved efficiency. However, some healthcare provider entities may be interfering with HIE across disparate and unaffiliated providers to gain market advantage. We propose a strategic gaming model for assessing hospital decision's to adopt HIE, which simulates an oligopolistic healthcare delivery market. When evaluating the behavior of hospitals under no federal incentive structures, our model suggests that less than six out of nine hospitals had market incentives to adopt HIE. Only medium-sized hospitals were not willing to adopt. Market incentives for hospitals to adopt HIE may be driven by reductions in repeat testing and hospital readmissions, as well as market share gains facilitated by a reduction of patient switching costs. Such market incentives, combined with HIE's ability to lower patient switching costs, [31] may be perceived by smaller hospitals as a threat for market share and thereby a barrier to adopting HIE. These results are aligned with empirical evidence suggesting that large hospital systems are more likely to have greater HIE capabilities than small and single practice providers. [16] Competition between hospitals, coupled with volume-based payment structures, create no incentives for smaller hospitals to exchange their data with competitors. [49–52] Although we believe the recent shift from volume- to value-based medicine may amplify the inherent value of HIE for all providers, medium-sized hospitals may need targeted actions to mitigate market incentives to not adopt HIE.

Consistent with economic theory, markets respond to market failures by developing structures that fill the gaps resulting from these failures. [53–56] Examples of recent structures include the value-based payment structure for hospitals and the HITECH Act. Particularly, the HITECH Act stimulates the use and exchange information, yet the effects of information exchange between healthcare providers can be conflicting. On the one hand, increased information exchange may improve hospital planning to the benefit of society and may help patients to make informed decisions. Further, increased information exchange may have a collusive potential to the benefit of hospitals but at the expense of the society as a whole. Market structures are not always successful in filling the gaps, but the political discussion regarding collusive efforts—health information blocking—are already taking place.

The Office of the National Coordinator for Health Information Technology recognizes health information blocking as an important and unexplored barrier for HIE. [13] Our results suggest that provider health information blocking, through collusions to not join an HIE network, is a significant barrier for nationwide interconnectivity of EMRs. We also found that current monetary incentives, as well as proposed penalties, had little to no effect on stimulating HIE in the region evaluated. Our results highlight the need for a new and comprehensive strategy to remedy health information blocking—current federal monetary incentives are not enough for some communities. Although a common practice of providers is to justify not adopting HIE due to privacy and data security concerns, there are reports of privacy laws being cited in situations in which they do not, in fact, impose restrictions. The Health Insurance Portability and Accountability Act (HIPAA) does not restrict patient data from being shared between providers. The HIPAA Privacy Rule only establishes national standards of privacy protections and rights, which applies to health plans, healthcare clearinghouses, and providers. The Rule requires appropriate safeguards to protect the privacy of personal health information, as well as setting limits and conditions on the uses and disclosures that may be made of such information without patient authorization. As long as patient consent is obtained, no further restrictions are imposed by HIPAA in a patient information transaction between providers. ONC is proposing to work with the Centers for Medicare & Medicaid Services to coordinate payment incentives and leverage other market drivers to reward interoperability and exchange, and to discourage health information blocking. Among several policy layers that are under discussion, new incentives to adopt HIE and penalties that raise the costs of not moving to interoperable health IT systems were proposed. In light of these debates, under particular market assumptions, our results suggest that penalties may be more effective than incentives to promote HIE adoption. Still abundant research is needed to estimate the optimal design of proposed HIE policy.

Study limitations and future research are discussed next. First, our research does not considers the physician opinion or willingness to use electronical medical records HIE, and thereby the model decides from a net economic perspective. We cannot assess the influence of healthcare providers on HIE hospital adoption. Second, our MSNE search method does not provide the one and unique equilibrium of a game; instead, the method finds the equilibrium out of many a game may have that is best in the sense that all players have optimized their payoffs rather than adjusted to their beliefs about other players in the game. Third, although out of the scope of this investigation, health information blocking behavior can also be generated by EMR vendors, or by coordinated actions between EMR vendors and their healthcare provider customers. Future work will study the role of competition in EMR developers market, and how their actors behave under different market structures. Finally, patients in our models can switch providers more easily than is the actual case due to the narrowness of networks. There are multiple factors influencing the patient health insurance purchase decision that, for the sake of simplicity, were compounded in a single parameter—the patient's personal preference. Since studying the complexities surrounding health insurance purchase are out of the scope of this investigation, we consider this as a limitation that will be address in future research.

6 Conclusion

A bi-level model for calculating oligopolistic HIE adoption equilibrium in healthcare provider markets has been developed and illustrated. The equilibrium is interpreted as the willingness of each hospital to share their patient data with competitors. Our research extends the existing evidence on HIE by incorporating network effects and the strategic behavior of a finite set of providers have at the time of deciding whether or not to adopt HIE. Using sample data from hospitals in Florida, we studied the potential impact of current and proposed HIE policy, as well as the impact of health information blocking in the willingness to adopt HIE. The proposed model can be used by policy makers to find incentive structures that will spur HIE adoption in a given community. HIE organizations can also benefit from our model by using it to prioritize their efforts to seek new customers by approaching those providers with higher likelihood of HIE engagement. Future work will analyze the dynamics of HIE adoption decisions over time, and extend the application of the model in evaluating other HIE networks and other markets where inter-organizational cooperation for the common good is essential.

Acknowledgments The authors would like to thank the three anonymous reviewers for their thoughtful revision.

Author's Contribution DM contributed to the idea conception, study design, model development, and acquisition and analysis of results. FF contributed to the study design, model development and analysis of results. SL, TD and JZ are guarantors and contributed to the idea conception and analysis of results. All authors contributed equally in preparing and reviewing multiple versions of the manuscript and provided significant intellectual content. All authors read and approved the final version of this manuscript.

Compliance with ethical standards

Competing interests The authors declare no competing interests.

Funding No funding was provided for the completion of this study.

References

1. Institute of Medicine (2000) *To Err Is Human: Building a Safer Health System*
2. Institute of Medicine(2001) *Crossing the Quality Chasm: A New Health System for the twenty-first Century.* Washington, DC
3. Rudin RS, Motala A, Goldzweig CL, et al. (2014) Usage and effect of health information exchange. Annals of Internal Medicine **161**: 803. doi:10.7326/M14-0877
4. Rahurkar S, Vest JR, Menachemi N (2015) Despite the spread of health information exchange, there is little evidence of its impact on cost, use, and quality of care. Health Aff (Millwood) 34:477–483. doi:10.1377/hlthaff.2014.0729

5. Furukawa MF, King J, Patel V, *et al.* (2014) Despite substantial progress in EHR adoption, health information exchange and patient engagement remain low in office settings. Health Aff (Millwood) hlthaff.2014.0445 –. doi:10.1377/hlthaff.2014.0445
6. Adler-Milstein J, DesRoches CM, Kralovec P, *et al.* (2015) Electronic health record adoption in US hospitals: progress continues, but challenges persist. Health Affairs
7. Leu MG, Cheung M, Webster TR, et al. (2008) Centers speak up: the clinical context for health information technology in the ambulatory care setting. Journal of General Internal Medicine 23:372–378. doi:10.1007/s11606-007-0488-6
8. Vest JR, Zhao H, Jasperson J, et al. (2011) Factors motivating and affecting health information exchange usage. Journal of the American Medical Informatics Association 18:143–149. doi:10.1136/jamia.2010.004812
9. Finnell JT, Overhage JM (2010) Emergency medical services: the frontier in health information exchange. *AMIA Annu Symp Proc* **2010**:222–226 http://www.pubmedcentral.nih.gov/articlerender.fcgi?artid=3041358&tool=pmcentrez&rendertype=abstract
10. Vest JR, Sean J'J, Zhao H, et al. (2011) use of a health information exchange system in the emergency care of children. BMC Medical Informatics and Decision Making **11**:78. doi:10.1186/1472-6947-11-78
11. Vest JR, Miller TR (2011) The association between health information exchange and measures of patient satisfaction. Appl Clin Inform 2:447–459. doi:10.4338/ACI-2011-06-RA-0040
12. Martinez DA, Mora E, Gemmani M, et al. (2015) Uncovering hospitalists' information needs from outside healthcare facilities in the context of health information exchange using association rule learning. Appl Clin Inform 6:684–697
13. Office of the National Coordinator for Health Information Technology. Report on Health Information Blocking. https://www.healthit.gov/sites/default/files/reports/info_blocking_040915.pdf
14. Adler-Milstein J, AK J (2014) Health information exchange among U.S. hospitals: who's in, who's out, and why? *Healthcare* **2**:26–32. doi:10.1016/j.hjdsi.2013.12.005
15. Adler-Milstein J, DesRoches CM, Jha AK (2011) Health information exchange among US hospitals. The American Journal of Managed Care 17:761–768 http://www.ncbi.nlm.nih.gov/pubmed/22832592
16. Miller AR, Tucker C (2014) Health information exchange, system size and information silos. Journal of Health Economics 33:28–42
17. Cohen E. (2010) Patients demand: 'Give us our damned data' CNN
18. CNN. (2010) Patients want records, hospitals turn deaf ear. CNN.com
19. Reps. D. Black and M. Honda. Letter to M. Tavenner and F. Mostashari. (2013) http://op.bna.com/hl.nsf/id/kcpk-99mnkx/$File/711EHRletter.pdf
20. White J. Halth IT Now Coalition. (2015).http://www.healthitnow.org/what-is-information-blocking/
21. Grossman JM, Kushner KL, November EA, *et al.* (2008) Creating sustainable local health information exchanges: can barriers to stakeholder participation be overcome?
22. Berman O, Zahedi F, KR P (2001) A decision model and support system for the optimal design of health information networks. *IEEE Trans Syst Man Cybern Part C (Applications Rev* **31**:146–158. doi:10.1109/5326.941839
23. Brennan PF, Ferris M, Robinson S, et al. (2005) Modeling participation in the NHII: operations research approach. *AMIA Annu Symp Proc AMIA Symp AMIA Symp* **2005**:76–80 http://www.ncbi.nlm.nih.gov/pubmed/16779005
24. Ferris M, Brennan PF, Tang L, et al. (2007) Creating operations research models to guide RHIO decision making. *AMIA Annu Symp Proc AMIA Symp AMIA Symp* **2007**:240–244 http://www.ncbi.nlm.nih.gov/pubmed/18693834
25. Sridhar S, Brennan PF, Wright SJ, et al. (2012) Optimizing financial effects of HIE: a multi-party linear programming approach. Journal of the American Medical Informatics Association 19:1082–1088. doi:10.1136/amiajnl-2011-000606
26. Merrill JA, Deegan M, Wilson RV, et al. (2013) A system dynamics evaluation model: implementation of health information exchange for public health reporting. Journal of the American Medical Informatics Association 20:e131–e138. doi:10.1136/amiajnl-2012-001289
27. Mustafee N, Katsaliaki K, Gunasekaran A, et al. (2013) Electronic health records: a simulation model to measure the adoption rate from policy interventions. Journal of Enterprise Information Management 26:165–182
28. Yaraghi N, AY D, Sharman R, et al. (2013) Network effects in health information exchange growth. ACM Trans Manag Inf Syst
29. Zhu Q, Gunter C, Basar T. (2012) Tragedy of anticommons in digital right management of medical records. In: *Proceedings of the 3rd USENIX conference on Health Security and Privacy*. 10
30. Desai S (2014) Electronic Health Information Exchange, Switching Costs, and Network Effects. *Switch Costs, Netw Eff NET Inst Work Pap*:2014
31. Strauss AT, Martinez DA, Garcia-Arce A, et al. (2015) A user needs assessment to inform health information exchange design and implementation. BMC Medical Informatics and Decision Making **15**: 81. doi:10.1186/s12911-015-0207-x
32. Ringel JS, Hosken SD, Vollaard BA, et al. (2002) http://www.rand.org/content/dam/rand/pubs/monograph_reports/2005/MR1355.pdf The Elasticity of Demand for Health Care: A review of the literature and its application to the military health system. Santa Monica, CA:
33. Sun H, Gao Z, Wu JA (2008) Bi-level programming model and solution algorithm for the location of logistics distribution centers. Applied Mathematical Modelling 32:610–616. doi:10.1016/j.apm.2007.02.007
34. Feijoo F, Das TK (2014) Design of Pareto optimal cap-and-trade policies for deregulated electricity networks. Applied Energy 119: 371–383. doi:10.1016/j.apenergy.2014.01.019
35. Fampa M, Barroso LA, Candal D, et al. (2007) Bilevel optimization applied to strategic pricing in competitive electricity markets. Computational Optimization and Applications 39:121–142. doi:10.1007/s10589-007-9066-4
36. Hu X, Ralph D (2007) Using EPECs to model bilevel games in restructured electricity markets with locational prices. Operations Research 55:809–827. doi:10.1287/opre.1070.0431
37. Li H, Zhang L, Jiao Y-C (2015) An interactive approach based on a discrete differential evolution algorithm for a class of integer bilevel programming problems. International Journal of Systems Science: 1–12. doi:10.1080/00207721.2014.993348
38. Saharidis GK, Ierapetritou MG (2009) Resolution method for mixed integer bi-level linear problems based on decomposition technique. Journal of Global Optimization 44:29–51. doi:10.1007/s10898-008-9291-0
39. Nash JF (1950) Equilibrium points in n-person games. Proceedings of the National Academy of Sciences 36:48–49. doi:10.1073/pnas.36.1.48
40. Pfuntner A, Wier LM, Steiner C. (2010) Costs for hospital stays in the united States. *Stat Br* **146**.
41. Overhage JM, Dexter PR, Perkins SM, et al. (2002) A randomized, controlled trial of clinical information shared from another institution. Annals of Emergency Medicine 39:14–23. doi:10.1067/mem.2002.120794
42. Blumenthal D (2009) Stimulating the adoption of health information technology. The New England Journal of Medicine:1477–1479. doi:10.1056/nejmp0901592 accessed 30 May2013
43. eHealth Initiative. (2007) Health Information Exchange: From Start-up to Sustainability. Washington, DC: http://www.hci3.org/sites/default/files/files/HRSA CCBH Final Report Revised.pdf

44. GAMS Development Corporation. (2013) General Algebraic Modeling System (GAMS)
45. Chatterjee B. (2009) An optimization formulation to compute Nash equilibrium in finite games. In: Methods and Models in Computer Science, 2009. ICM2CS 2009. Proceeding of International Conference on. 1–5
46. The MathWorks Inc. (2012) MATLAB
47. Braess PDDD (1968) Über ein Paradoxon aus der Verkehrsplanung. *Unternehmensforschung* **12**:258–268
48. Baker L (2009) Removing roads and traffic lights speeds urban travel. Scientific American:20–21
49. Kruse CS, Regier V, Rheinboldt KT, et al. (2014) Barriers over time to full implementation of health information exchange in the United States. *JMIR*. Medical Informatics **2**:e26. doi:10.2196/medinform.3625
50. Sheikh A, Sood HS, Bates DW (2015) Leveraging health information technology to achieve the 'triple aim' of healthcare reform. Journal of the American Medical Informatics Association 44:1–9. doi:10.1093/jamia/ocv022
51. O'Malley AS, Bond AM, Berenson RA (2011) Rising hospital employment of physicians: better quality, higher costs? *Issue Br Cent Stud Heal Syst Chang*:1–4 http://www.ncbi.nlm.nih.gov/pubmed/21853632
52. O'Malley AS. (2015) Testimony to the interoperability task force of the health IT policy committee, ONC
53. Greenwald BC, Stiglitz JE (1986) Externalities in economies with imperfect information and incomplete markets. Quarterly Journal of Economics:229–264
54. Vives X (2002) Private information , strategic behavior , and efficiency in Cournot markets. *RAND*. Journal of Econometrics:361–376
55. Gal OE (1985) Information Sharing in Oligopoly. *Econometrica*: 329–343. doi:10.2307/1911239
56. Raith MA. (1993) A general model of information sharing in oligopoly. *LSE STICERD Res Pap No TE260*