Modeling and Designing Health Care Payment Innovations for Medical Imaging

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Abstract Payment innovations that better align incentives in health care are a promising approach to reduce health care costs and improve quality of care. Designing effective payment systems, however, is challenging due to the complexity of the health care system with its many stakeholders and their often conflicting objectives. There is a lack of mathematical models that can comprehensively capture and efficiently analyze the complex, multi-level interactions and thereby predict the effect of new payment systems on stakeholder decisions and system-wide outcomes. To address the need for multi-level health care models, we apply multiscale decision theory (MSDT) and build upon its recent advances. In this paper, we specifically study the Medicare Shared Savings Program (MSSP) for Accountable Care Organizations (ACOs) and determine how this incentive program affects computed tomography (CT) use, and how it could be redesigned to minimize unnecessary CT scans. The model captures the multi-level interactions, decisions and outcomes for the key stakeholders, i.e., the payer, ACO, hospital, primary care physicians, radiologists and patients. Their interdependent decisions are analyzed game theoretically, and equilibrium solutions - which represent stakeholders’ normative decision responses - are derived. Our results provide decision-making insights for the payer on how to improve MSSP, for ACOs on how to distribute MSSP incentives among their members, and for hospitals on whether to invest in new CT imaging systems.

Keywords Multiscale decision theory · Health care incentives · Health care payment systems · Accountable Care Organizations · Medicare Shared Savings Program · Medical technology

1 Introduction

A major contributor to health care costs in the United States (U.S.) is the high number of medical tests and procedures performed, in particular, those involving advanced and costly technologies. For example, imaging technologies, such as computed tomography (CT), are frequently administered in cases for which they are not clinically indicated or for which less expensive alternatives exist (e.g., ultrasound) [1]. They not only drive up health care costs but also expose patients to harmful radiation and image misinterpretations.

A root cause for medical technology overuse is the fee-for-service (FFS) reimbursement system, which reimburses providers based on the quantity not quality of care. To promote care coordination and contain costs, payers have been exploring a variety of payment innovations [2]. Among them, the Medicare Shared Savings Program (MSSP) for Accountable Care Organizations (ACOs), administered by the Centers for Medicare and Medicaid Services (CMS), has received considerable attention [3,4]. Under MSSP, ACOs and its members, e.g., hospitals, primary care physicians and radiologists, continue to receive standard Medicare reimbursements, plus an incentive based on cost savings and quality targets [5].

MSSP for ACOs is being field tested since 2012. Recently published data [6] suggests that the MSSP ACO model has been overall effective in reducing cost of care. However, CMS’s choice of certain program pa-
rameters, such as the cost benchmark, has been criticized for lacking sufficient justification from model-based or data-driven findings [7]. Meanwhile, a high variability in ACO performance exists [8]. ACOs use different ways to incentivize their members to strive towards better care coordination and cost reductions. Since CMS has not developed any guidelines for shared savings re-distribution, and since ACOs are reluctant to publicly share sensitive business information, mathematical models are the next best approach for analyzing and designing effective ACO-internal incentive distribution mechanisms and providing decision guidance for ACOs and individual providers.

In this paper, we develop a mathematical model to analyze and improve MSSP with a focus on CT scan use. We address the challenge of modeling and analyzing the interdependent decisions of health care stakeholders by using multiscale decision theory (MSDT). We derive insights for the payer on how MSSP and the cost benchmark affect stakeholders’ decisions. Our results also inform ACOs on how to optimally distribute MSSP incentives. By applying and advancing MSDT, this paper makes contribution to management science and the modeling of complex, multi-stakeholder, socio-technical systems. Moreover, the paper provides decision-making insights for stakeholders and policy insights on an important and timely health care topic.

2 Related Work

A number of mathematical approaches have been developed to study health care payment systems and to design incentive-based contracts. Fuloria and Zenios [9] developed an outcomes-adjusted payment system based on a principal-agent model that consists of prospective payments and retrospective quality adjustments. Building upon this model, Lee and Zenios [10] used empirical data from Medicare’s end-stage renal disease program and showed the effectiveness of this payment system. Yaesoubi [11] analyzed contract coordination mechanisms for preventive medical care with win-win-wins for payers, providers and patients. Boadway et al. [12] proposed a mixed DRG-FFS reimbursement contract and analyzed its effect on the interactions between payer and hospital, as well as hospital and physicians. Pope et al. [13] proposed multilateral contracts between payers, providers and patients, and compared the contracts with bilateral agreements in terms of cost and quality of care.

As an alternative to these analytical models, simulations have been used to study payment modalities and incentives [14–16]. Simulations are well suited to model the complex health care system and study emergent phenomena. However, generalizable insights are difficult to obtain, and robust results require extensive computational studies.

For MSSP, only few quantitative studies or mathematical models have been developed to evaluate its effects on stakeholder decisions and outcomes [17,18]. In our paper, we build upon the work by Zhang, Wernz et al. [19] in which a first MSDT model for MSSP and diagnostic imaging was developed. Compared with this prior study, the paper at hand considers the difference between CT-scan-prescribing physicians and radiologists and extends the previous MSDT model by explicitly accounting for radiologists. Further, a number of modeling assumptions were removed to more realistically capture how diagnostic imaging decisions are made by physicians, how screening decisions are made by radiologists, and how these decisions affect system-level outcomes. Lastly, the paper presents the first analytical health care model with four decision-making agents. Existing models account for merely two or at best three agents due to the mathematical complexities and challenges involved.

MSDT was first developed by Wernz [20] as an analytical modeling approach that can capture multi-agent interactions across system levels and time scales. It has been applied to production planning [21,22], service enterprise management [23–25], supply chain management [26], and - as just discussed - health care [19]. However, all of these papers focused on developing the MSDT methodology, with the applications serving as illustrative examples. This paper is the first application-oriented work that builds upon the MSDT foundations laid by prior work.

3 The Model

3.1 Problem Description

We consider six key stakeholders: payer, ACO, hospital, primary care physicians, radiologists and patients. We assume that patients follow physicians’ diagnostic and treatment recommendations. Moreover, we assume that the hospital is the leader of the ACO and makes the incentive distribution decisions. Lastly, we only account for the aggregate behaviors of primary care physicians and radiologists, and model each group as a single agent. Thus, we are left with four decision-making agents, which we refer to as CMS (payer), agent H (hospital/ACO), agent P (primary care physicians) and agent R (radiologists). The agents and their decisions are summarized in a decision tree in Figure 1.
agents P and R use the mental model of assigning a rank \( \in [0,1] \) to each patient in their population \( i = 1, 2 \), such that a patient with a higher rank is healthier showing less severe symptoms (population 1) or has a lower disease predisposition (population 2). We assume that patient rank is uniformly distributed across the patient populations with \( x_i \sim U(0,1) \). The rank concept was adopted from Yaesoubi and Roberts [11].

Lower ranked patients have a greater probability \( p_1(x_i) \) of having a disease. We assume that agents P and R can assess this probability and assign their rank values accordingly. Rank and probability of disease are inversely related. For patients in population 1, a rank of 0 means 100% sick, while a patient with rank 1 has a zero probability of being sick. For values in between, we assume a linear relationship. Rank is therefore assigned such that \( p_1(x_1) = 1 - x_1 \) for population 1. For population 2, we include a scale factor \( r \in [0,1] \) to account for the fact that even patients with the highest predisposition for a disease (rank 0), only have a probability of \( r \) of having the disease. Consequentially, the probability of having a disease is \( p_2(x_2) = r \cdot (1 - x_2) \).

Depending on the rank, a diagnostic or screening CT test for a patient is medically more or less justified [28]. We assume that agents P and R have established a testing threshold \( \theta_P \) and \( \theta_R \), respectively. The threshold corresponds to the probability of disease at which the physician is indifferent between performing and not performing a test [29]. Having observed rank \( x_1 \), agent P orders CT tests only for sick patients with \( x_1 \leq \theta_P \), and agent R only for at-risk patients with \( x_2 \leq \theta_R \). For patients with \( x_1 > \theta_P \) or \( x_2 > \theta_R \), no CT scan is ordered. At an aggregate patient level, the thresholds \( \theta_P \) and \( \theta_R \) correspond to the CT testing percentage of population 1 and 2, respectively.

### 3.2 CT Scan Decision Problem

Agents P and R determine whether a CT scan is necessary based on patient conditions. We assume that agents P and R use the mental model of assigning a rank \( x_i \in [0,1] \) to each patient in their population \( i = 1, 2 \), consisting of patients that show certain symptoms and seek medical diagnosis and treatment. The second type serves population 2, consisting of patients that are asymptomatic but are at risks of developing a disease and for whom preventive screenings may be beneficial. A clinical example for population 1 are men who have pain during urination and for whom an abdominal CT scan could detect kidney stones. An example for population 2 are asymptomatic women who may benefit from regular screening mammograms [27]. The two populations are assumed to be disjoint sets. The number of patients in population 1 and 2 are denoted by \( N_1, N_2 \), respectively.

#### 3.2.1 Diagnostic CT Scans

Diagnostic CT scans for population 1 are ordered by agent P and are interpreted by agent R. Agent P’s problem is to determine the optimal testing threshold \( \theta_P \) to maximize a two-attribute utility function consisting of health benefit and monetary payoff.

We define the state space of each patient as a 3-tuple [30], with \( \{\text{true health status, imaging decision, treatment decision}\} \). We consider binary states, with true health status being either S (sick) or H (healthy); the physician’s imaging decision as either I (imaging) or A (alternative, no imaging); and the treatment decision as either T (will be treated) or N (no immediate treatment). We assume that without an imaging test, no diagnosis will be made, and a wait-and-see approach (no immediate treatment) is chosen. Hence, the states \( \{S, A, T\} \) and \( \{H, A, T\} \) do not exist.
Both correct diagnosis and misdiagnosis are possible after a CT scan. The probability of a correct diagnosis is \( q \), which is influenced by the quality of the medical technology used. We assume that the probability of a correct diagnosis is greater than that of a misdiagnosis, i.e., \( q \in (0.5, 1) \). Treatments will be performed only when positive results are found through imaging. Table 1 summarizes the probabilities for a patient with rank \( x_1 \) transitioning to one of the six possible states.

**Health benefit:** We denote the health benefit for each patient state by value \( \mu \). We order the health benefit values according to the patient’s states based on the following observations: treatment for sick people is effective (\( \mu_{S,I,T} > \mu_{S,I,N} \) and \( \mu_{S,I,T} > \mu_{S,A,N} \)); treatment for healthy people has side effects (\( \mu_{H,I,N} > \mu_{H,I,T} \) and \( \mu_{H,A,N} > \mu_{H,I,T} \)); imaging tests have side effects (\( \mu_{S,A,N} > \mu_{S,I,N} \) and \( \mu_{H,A,N} > \mu_{H,I,N} \)); treating or imaging a healthy person is less harmful than ignoring a sick person (\( \mu_{H,I,T} > \mu_{S,I,N} \) and \( \mu_{H,I,T} > \mu_{S,A,N} \); \( \mu_{H,I,N} > \mu_{S,I,N} \) and \( \mu_{H,I,N} > \mu_{S,A,N} \)); and the health benefits of treating a person correctly, i.e., no imaging/treatment when healthy and imaging/treatment when sick, are the same (\( \mu_{H,A,N} = \mu_{S,I,T} \)). Taken together, the health status values can be ordered as \( \mu_{H,A,N} > \mu_{S,I,T} > \mu_{H,I,N} > \mu_{H,I,T} > \mu_{S,I,N} > \mu_{S,A,N} \).

**Monetary payoff:** Agents P and R are reimbursed based on an FFS basis according to the Outpatient Prospective Payment System (OPPS) (not accounting for incentives). Agent R receives a fixed payment \( c_I \) per test for the effort of interpreting test results. Agent P does not receive direct payments associated with CT tests. Instead, agent P’s payment is FFS reimbursement resulting from downstream diagnoses based on CT tests and treatments. Depending on the patient state and OPPS fee schedule, agent P receives monetary payoffs, which can be ordered as follows: \( c_{H,I,T} = c_{S,I,T} > c_{H,I,N} = c_{S,I,N} > c_{H,A,N} = c_{S,A,N} = 0 \). Agent P receives the highest reimbursement when both a CT test and downstream treatment are performed, and receives the second highest reimbursement when only a CT test but no downstream treatment is performed. We set the reimbursement to be 0 when neither a CT test nor treatment is performed.

The decision process of diagnostic imaging, and the associated probability and payoffs can be summarized in a decision tree (Figure 2).

### 3.2.2 CT Scans for Disease Screening

The preventive screening tests for population 2 are ordered and interpreted by agent R only. Similar to agent P, agent R’s problem is to determine the optimal screening testing threshold \( \theta_R \) for population 2, maximizing its utility. Following the process in Section 3.2.1, we can define the transition probabilities for a patient with rank \( x_2 \) transitioning to one of the six states in the same way as in Table 1.

**Health benefit:** The health benefit values associated with patient states are as before: \( \mu_{H,A,N} = \mu_{S,I,T} > \mu_{H,I,N} > \mu_{H,I,T} > \mu_{S,A,N} > \mu_{S,I,N} \).

**Monetary payoff:** A fixed payment \( c_I \) per test is given to agent R for the effort of interpreting CT test results. Agent P does not receive any payments in this case. The decision process of screening imaging follows that of Figure 2.

### 3.3 CT Scanner Investment Decision

Agent H decides whether to upgrade its current CT scanner. The agent’s decision variable \( a_h \) is binary with \( a_1 \) (buy advanced CT scanner) and \( a_2 \) (status quo). The decision leads to an action-dependent investment cost, either \( k(a_1) = k_1 \) or \( k(a_2) = k_2 = 0 \). Further, agent H’s decision results in an uncertain outcome of maintenance costs. The state space of agent H’s maintenance cost is denoted by \( S = \{ s_1, s_2 \} \), referring to high cost and low cost, respectively. The state-dependent maintenance cost is denoted by \( c^H(s_a) \). The uncertainties between agent H’s actions and states are denoted by discrete transition probabilities \( Pr(s_a|a_h) = \alpha_{a,h} \).

From a medical perspective, the purchase of a new and more advanced CT scanner improves imaging diagnosis accuracy. To capture this interdependency, the probability of correct diagnosis \( q \) is modified by \( \delta \), with \( \delta \in (0, 1) \), such that the resulting probability is

\[
q(a_h) = \begin{cases} 
q + \delta, & \text{if } h = 1 \\
q, & \text{if } h = 2
\end{cases}
\]
3.4 Utility Functions of Agents

We use the detailed graphical representation in MSDT to illustrate the interdependencies among agents’ decisions and outcomes, thereby connecting the three system levels. In Figure 3, the red arrows represent the interdependencies among agents. Interdependency 1 is the influence of agent H’s investment decision on agents P and R’s transition probabilities, expressed by Eq. 1. Interdependency 2 is the influence of agents P and R’s outcomes on agent H’s outcome (see later Section 3.4.3 for the mathematical formulation).

We assume that each agent cares about its own payoff but also patients’ well-being. Therefore, agents maximize their utility functions that consist of a monetary payoff and a health benefit component. Next, we discuss the utility function of each agent (not yet accounting for incentives, which are analyzed in Section 4).

3.4.1 Agent P

Agent P cares about its monetary payoff, denoted by $P^{P1}$, and the well-being of its patients, expressed by the aggregated health benefit $B^{P1}$. We express agents’ utilities in terms of monetary payoffs. To convert the health benefit $B^{P1}$ into a monetary payoff and to account for agent P’s weighting of the two attributes, we use a scaling factor $\lambda^P > 0$ for $B^{P1}$, $\lambda^P$ represents the agent’s willingness-to-pay (WTP) for health, and is defined as the dollar amount an agent is willing to trade for one unit of health benefit [11]. Estimation methods for an agent’s WTP include quality-adjusted life-year (QALY) measures [31] and the survey-based contingent valuation method [32].

We assume risk neutrality and linear monetary preferences. Agent P’s decision problem is to choose diagnostic testing threshold $\theta_P$, given agent H’s investment decision $a_h$, that maximizes its utility $U^P$, i.e.,

$$\max_{0 \leq \theta_P \leq 1} U^P(\theta_P|a_h) = \Pi^{P1}(\theta_P|a_h) + \lambda^P \cdot B^{P1}(\theta_P|a_h).$$

(2)

3.4.2 Agent R

Agent R’s utility depends on both the diagnostic testing threshold $\theta_P$ for population 1 and the screening testing threshold $\theta_R$ for population 2. From population 1, agent R obtains only FFS payment for test interpretation, denoted by $R^{P1}$ (\theta_P). From population 2, agent R obtains monetary payoff $R^{P2}(\theta_R)$ and aggregated health benefit $B^{R2}(\theta_R)$. Agent R’s decision problem and utility function (with scaling factor $\lambda^R > 0$) is

$$\max_{0 \leq \theta_R \leq 1} U^R(\theta_R, \theta_P|a_h) = \Pi^{R1}(\theta_P) + \Pi^{R2}(\theta_R) + \lambda^R \cdot B^{R2}(\theta_R|a_h).$$

(3)

3.4.3 Agent H

Agent H’s decision problem is to make an investment decision $a_h$ that maximizes its utility, consisting of its monetary payoff and patients’ health benefits (with scaling factor $\lambda^H > 0$):

$$\max_{a_h} U^H(a_h) = \Pi^H(a_h) + \lambda^H \cdot [B^{P1}(\theta_P) + B^{R2}(\theta_R)].$$

(4)

Agent H’s monetary payoff $\Pi^H$ is revenue minus costs. Each imaging test ordered by agents P or R incurs a fixed payment (revenue) to agent H according to OPPS and a fixed operating cost. To map interdependency 2, we introduce the associated payment coefficient $\gamma_p \geq 0$ and the associated cost coefficient $\gamma_c \geq 0$, such that agent H’s revenue is $\gamma_p \cdot c_I$ and its
cost is $\gamma_c \cdot c_I$, with $c_I$ being the payment that agent $R$ received. Along with the action-dependent cost $k(a_h)$ and the state-dependent cost $c^H(s_a)$ described previously, agent H’s monetary payoff is

$$\Pi^H(a_h) = \sum_a -c^H(s_a) \cdot \Pr(s_a|a_h) - k(a_h) + (\gamma_p - \gamma_c) \cdot [\Pi^R_1(\theta_P) + \Pi^R_2(\theta_R)].$$

(5)

### 3.4.4 CMS

CMS aims to maximize social welfare, which consists of the total billings paid out to the ACO, the MSSP incentive, and the health benefit of all patients. The utility function is

$$\max_M U^{CMS}(M) = -\Pi^{ACO} - I + \lambda^{CMS} \cdot [B^{P1}(\theta_P) + B^{R2}(\theta_R)].$$

(6)

Specifically, the total billings of the ACO are $\Pi^{ACO} = \gamma_p [\Pi^{R1}(\theta_P) + \Pi^{R2}(\theta_R)] + \Pi^{P1}(\theta_P) + \Pi^{R1}(\theta_P) + \Pi^{R2}(\theta_R)$. Additionally, the ACO receives a share $\eta \in (0, 1]$ of the difference between their Medicare billings and the cost benchmark $M$ set by CMS as the total incentive. Billings above the benchmark result in a penalty for the ACO (negative incentive); billings below the benchmark result in a reward (positive incentive). Hence, the total incentive received by the ACO is

$$I(\cdot) = \eta \cdot \left[ M - \gamma_p \cdot [\Pi^{R1}(\theta_P) + \Pi^{R2}(\theta_R)] - \Pi^{P1}(\theta_P) - \Pi^{R1}(\theta_P) - \Pi^{R2}(\theta_R) \right].$$

(7)

## 4 Analysis

We analyze and compare two scenarios - (1) without incentive, and (2) with incentive - to examine the multi-level interdependencies and MSSP’s effects. To find the agents’ optimal decisions in their sequential game (recall Figure 1), we use the subgame perfect Nash equilibrium (SPNE) concept [33] and the backward induction method. We denote the optimal decisions without incentives by superscript * and with incentives by superscript **.

### 4.1 No Incentive

Without incentives, the following sequence of events occurs: (1) agent H chooses the optimal investment decision $\theta_h^*$; (2) given $\theta_h^*$, agent P and agent R decides the optimal CT testing threshold $\theta_P^*$ and $\theta_R^*$ simultaneously.
4.1.1 Stage 2: Agents P and R’s Decision

Given an investment decision \( a_h \), agents P and R chooses a testing threshold \( \theta_P^* \) and \( \theta_R^* \) to maximize its own utility, i.e.,

\[
\theta_P^* = \arg \max_{\theta_P \in [0, 1]} [H^{P1}(\theta_P | a_h) + \lambda^P \cdot B^{P1}(\theta_P | a_h)]. \tag{8}
\]

\[
\theta_R^* = \arg \max_{\theta_R \in [0, 1]} [H^{R1}(\theta_P) + H^{R2}(\theta_R) + \lambda^R \cdot B^{R2}(\theta_R | a_h)]. \tag{9}
\]

The detailed representation of the utility maximization problems (UMPs) of agents P and R (Eq. 8, 9) can be found in Appendix.

We assume that in each of the patient populations \( N_1 \) and \( N_2 \), at least one, but not all patients require a CT scan from a medical standpoint. This implies that if agents P and R only cared about patient health, but not monetary payoffs, their optimal scan would not be 0 or 1.

Next, we define that for agents P and R that care only about patient health, the health-maximizing CT testing thresholds are \( \theta_P^h \) and \( \theta_R^h \). For agents P and R that care only about monetary payoffs, the optimal monetary-maximizing thresholds are \( \theta_P^m \) and \( \theta_R^m \). For agents that care about both monetary payoffs and patient health, the optimal testing thresholds are \( \theta_P^* \) and \( \theta_R^* \). The following theorem provides closed-form solutions for the optimal testing thresholds.

**Theorem 1** The optimal testing thresholds always lie between the monetary-maximizing threshold and the health-maximizing threshold, i.e., \( \theta_P^m < \theta_P^* \leq \theta_P^h = 1 \) and \( \theta_R^m < \theta_R^* \leq \theta_R^h = 1 \). Specifically,

\[
\theta_P^* = \frac{(c_{S,A,N} - \bar{q}c_{S,I,T} - (1 - \bar{q})c_{S,I,N})}{(1 - 2\bar{q})(c_{H,I,T} - c_{H,I,N}) + \lambda^P[\mu_{S,A,N} - \bar{q}\mu_{S,I,T} - (1 - \bar{q})\mu_{S,I,N}]} + \frac{\lambda^P[\mu_{H,A,N} - \bar{q}\mu_{H,I,T} - (1 - \bar{q})\mu_{H,I,N}]}{(1 - 2\bar{q})(c_{H,I,T} - c_{H,I,N}) + \lambda^P[\mu_{H,A,N} - \bar{q}\mu_{H,I,T} - (1 - \bar{q})\mu_{H,I,N}]} \tag{10}
\]

\[
\theta_R^* = 1 + \frac{\lambda^R[\mu_{H,A,N} - \bar{q}\mu_{H,I,T} - (1 - \bar{q})\mu_{H,I,N}]}{(1 - 2\bar{q})(\mu_{H,A,N} - \mu_{H,I,T}) + \lambda^R[\mu_{H,A,N} - \bar{q}\mu_{H,I,T} - (1 - \bar{q})\mu_{H,I,N}]} \tag{11}
\]

**Proof** See Appendix.

Theorem 1 implies that with the knowledge of parameters in Eq. 10, agent P does not have to know agent R’s decision \( \theta_R \) in order to choose the optimal testing threshold \( \theta_P^* \). Similarly, agent R can derive \( \theta_R^* \) based on Eq. 11 without knowing \( \theta_P \). Theorem 1 further shows that if agents P and R are financially rewarded for doing more tests - as under FFS - both agents will perform more imaging tests than medically indicated. In the extreme case where an agent is solely financially motivated and does not care about patient health, the agent would perform CT scans on all patients.

4.1.2 Stage 1: Agent H’s decision

Agent H chooses the investment decision \( a_h^* \) to maximize its utility, i.e.,

\[
a_{h}^{*} = \arg \max_{a_{h}} [H^{H}(a_{h}) + \lambda^{H} \cdot B^{H}]
\]

Agent H considers the impact of its decision on the later decisions by agents P and R. By accounting for the optimal thresholds at Stage 2, agent H’s utility function becomes

\[
U^{H}(a_{h}) = \sum_{a} -c^{H}(s_{a}) \cdot \Pr(s_{a}|a_{h}) - k(a_{h}) + (\gamma_{p} - \gamma_{c}) \cdot [H^{R1}(\theta_{P}^{*}) + H^{R2}(\theta_{R}^{*})] + \lambda^{H} \cdot [B^{P1}(\theta_{P}^{*} | a_{h}) + B^{R2}(\theta_{R}^{*} | a_{h})].
\]

We obtained the closed-form solution for Eq. 12 through differentiation, however, the resulting equation is too large to effectively display or interpret in its analytical form. To still provide insights on agent H’s CT scanner investment decision, we performed a numerical analysis in Section 5. The numerical analysis shows how parameters such as investment cost, maintenance cost, and health benefits affect the investment decision. We can, however, provide analytical solutions on how CT testing thresholds are affected by agent H’s investment decision.

**Theorem 2** (a) When agent H’s decision switches from status quo \((a_{2})\) to buy advanced CT scanner \((a_{1})\), the health-maximizing thresholds \( \theta_{P}^{h} \) and \( \theta_{R}^{h} \) of agent P and R will both increase.

(b) If agent P cares about both monetary payoffs and patient health, the CT testing threshold increasing condition \( \theta_{P}^h(a_{2}) < \theta_{P}^h(a_{1}) \) only holds if \( \theta_{R}^h(a_{2}) < 1 \) and

\[
c_{H,I,N}^2 - c_{H,I,T}^2 - \lambda^2 \mu_{H,I,N} \mu_{S,A,N} + \mu_{H,I,T} \mu_{S,A,N} + \mu_{H,I,N} \mu_{S,I,N} - \mu_{H,I,T} \mu_{S,I,T} - \mu_{S,A,N} \mu_{S,I,T} + \mu_{S,I,N}^2 - \lambda^2 \phi_{H,I,T} (\mu_{S,A,N} - \mu_{H,I,T}) + \mu_{H,I,N} (\mu_{H,I,N} - \mu_{S,I,T} - \mu_{S,A,N} + \mu_{S,I,N}) > 0. \tag{14}
\]
(c) If agent \( R \) cares about both monetary payoffs and patient health, the condition \( \theta_R(a_2) < \theta_R(a_1) \) always holds (given that \( \theta_R(a_2) < 1 \)).

**Proof.** See Appendix.

Theorem 2(a) and 2(c) confirm the intuition that CT testing thresholds increase with better technology, due to the improved health outcomes. Theorem 2(b), however, states that an increase in the CT testing threshold by the primary care physicians only occurs under certain conditions, and may decrease due to improved technology. The reason is that agent \( P \)'s monetary payoff decreases with better diagnostic capabilities. This decrease can be explained as follows. We have assumed that ignoring a sick patient has worse health outcomes than treating a healthy patient. Therefore, agent \( P \) is more inclined to test and treat a patient that may be healthy than to ignore a patient that may be sick. In combination with better CT diagnostics, the reduction of false positive results is greater than the reduction of false negative results. Meanwhile, unlike agent \( R \), agent \( P \)'s monetary payoff depends not only on imaging tests but also on downstream treatments. A switch from false positives to true negatives decreases agent \( P \)'s monetary payoff \((c_{H,I,T} > c_{H,I,N})\), and a switch from false negatives to true positives increases the monetary payoff \((c_{S,I,N} < c_{S,I,T})\). Moreover, the total payoff reduction of the former is more significant than the total payoff increase of the latter. Hence, given an advanced CT scanner, a higher testing threshold improves health outcomes, but decrease monetary payoffs. Therefore, higher testing thresholds due to better CT diagnostics only occur if agent \( P \) puts a relatively greater emphasis on patient health than on monetary payoffs (large \( \lambda^P \)).

4.2 With Incentive

With MSSP incentives, the following sequence of events occurs: (1) CMS decides and announces the MSSP program, specifically the sharing percentage \( \eta \in (0, 1] \) and the cost benchmark \( M \); (2) agent \( H \) chooses the optimal investment decision and the optimal incentive distribution parameters for the ACO members; (3) agents \( P \) and \( R \) decide their optimal CT testing thresholds. We assume that agent \( H \) chooses incentive sharing percentages \( \alpha \) and \( \beta \) for agents \( P \) and \( R \), respectively, for the redistribution of the incentive \( I \) it receives from CMS. The incentives for the three agents are \( I^P = \alpha I \), \( I^R = \beta I \), and \( I^H = (1 - \alpha - \beta) I \), with \( 0 \leq \alpha, \beta \leq 1 \), \( 0 \leq \alpha + \beta \leq 1 \).

4.2.1 Stage 2: Agents \( P \) and \( R \)'s decision

Given the decisions by CMS and agent \( H \), agents \( P \) and \( R \) choose the optimal testing thresholds \( \theta_{P}^{**} \) and \( \theta_{R}^{**} \):

\[
\theta_{P}^{**} = \arg \max_{\theta_P \in [0, 1]} [I^P(\theta_P|a_h) + \lambda^P \cdot B^{P1}(\theta_P|a_h) + I^P].
\]  

(15)

\[
\theta_{R}^{**} = \arg \max_{\theta_R \in [0, 1]} [I^R1(\theta_R) + I^R2(\theta_R) + \lambda^R \cdot B^{R1}(\theta_R|a_h) + I^R].
\]  

(16)

**Theorem 3** (a) Given incentives and no switch in agent \( H \)'s investment decision \( a_h^* \), agent \( P \)'s optimal testing threshold \( \theta_{P}^{**} \) is a strictly decreasing function of the sharing percentage \( \alpha \) for \( \theta_{P}^{*} \in (0, 1) \). Likewise, \( \theta_{R}^{**} \) is a strictly decreasing function of \( \beta \) for \( \theta_{R}^{*} \in (0, 1) \).

(b) Given an identical investment decision in the incentive and no incentive scenario \( a_h^* = a_h^{**} \), it always holds that \( \theta_{P}^{**} \leq \theta_{P}^{*} \) and \( \theta_{R}^{**} \leq \theta_{R}^{*} \).

**Proof.** See Appendix.

The mathematical expressions of \( \theta_{P}^{**} \) and \( \theta_{R}^{**} \) are included in the Appendix. We find again that agent \( P \) can derive \( \theta_{P}^{**} \) without the knowledge of \( \theta_{R} \), and that agent \( R \) can derive \( \theta_{R}^{**} \) without knowing \( \theta_{P} \). Further, the expressions of \( \theta_{P}^{**} \) and \( \theta_{R}^{**} \) do not contain the cost benchmark \( M \), which means a change in the benchmark does not affect the optimal CT testing thresholds. The optimal testing thresholds being independent of \( M \) may surprise at first, since one may expect that a higher incentive payment would reduce CT testing thresholds. This, however, is not the case, since the net incentives, i.e., incentives minus losses in revenue, do not change for agents \( P \) and \( R \) with changes in \( M \). The net incentives do however change with the sharing percentages, as discussed in Theorem 3(a).

Theorem 3(a) confirms the intuition that the larger the sharing percentage, the larger the reduction in test ordering. The reasons why CT testing thresholds are affected by \( \alpha \) and \( \beta \) is that the incentive is proportional to the sharing percentages. Theorem 3(b) confirms that MSSP incentives can reduce the number of CT tests ordered by agents \( P \) and \( R \). Therefore, MSSP is an effective mechanism to address CT scan overuse that stems from FFS payments.

4.2.2 Stage 1: Agent \( H \)'s decision

Agent \( H \) chooses the optimal investment decision \( a_h^* \) and the optimal sharing percentages \( \alpha^{**} \) and \( \beta^{**} \) to
maximize its utility. Agent H’s UMP is

\[
\max_{a_h, \alpha, \beta} U^H(a_h, \alpha, \beta) = \Pi^H(a_h) + \lambda^H \cdot B^H + (1 - \alpha - \beta) I
\]

s.t. \(0 \leq \alpha \leq 1, \quad 0 \leq \beta \leq 1, \quad 0 \leq \alpha + \beta \leq 1.
\]

(17)

In the analysis of Stage 2, we showed that the cost benchmark \(M\) does not affect \(\theta_P^{**}\) and \(\theta_R^{**}\) directly. However, the analysis of Stage 1 with UMP 17 shows that \(M\) affects agent H’s optimal decisions \(a_h^{**}\), \(\alpha^{**}\) and \(\beta^{**}\). Given that these decisions in turn affect \(\theta_P^{**}\) and \(\theta_R^{**}\), we now refine our earlier result and state that in a 2-stage game with optimal decision response by all agents, the cost benchmark \(M\) affects agents P and R’s CT scan decisions indirectly.

UMP 17 is a constrained optimization problem with numerous parameters and nonlinearities; hence closed-form solutions for \(a_h^{**}\), \(\alpha^{**}\) and \(\beta^{**}\) cannot be derived. Nevertheless, the global optima can be determined with low computational effort for concrete parameter values.

Next, we provide numerical solutions to agent H’s UMP and discuss how the cost benchmark \(M\) affect agent H’s decisions and the optimal testing thresholds \(\theta_P^{**}\) and \(\theta_R^{**}\).

5 Numerical analysis

Our numerical analysis is based on parameter values listed in the Appendix. Mathematica® is used for all calculations. We follow the backward induction principle [33] and first calculate agents P and R’s optimal decision response (Stage 2), followed by agent H’s optimal decision (Stage 1). We start with investigating the equilibrium solutions for a fixed cost benchmark. Thereafter, we vary the benchmark to analyze its effect.

5.1 Base Case: Optimal Decisions of Agents H, P and R

We assume the cost benchmark to be \(M=3700\) and determine the agents’ optimal decisions and their utility values. The results of no incentive scenario and the MSSP incentive scenario are summarized in Table 2. The agents’ optimal decisions are underlined and the decision relevant utility values are in bold.

In both scenarios, with and without incentives, agent H prefers to make the CT scanner investment, since \(U^H^{**}(a_1) > U^H(a_2)\). In this 2-stage game, agent H’s utility depends on agent P and R’s optimal decision response to agent H’s decision. Agent P and R’s CT testing thresholds are higher with agent H’s CT scanner investment compared to the status quo: \(\theta_P^{**} > 0.947, \theta_R^{**} = 0.738 > 0.700\); and \(\theta_P^{**} = 0.942 > 0.941\) and \(\theta_R^{**} = 0.542 > 0.503\). Agents P and R also prefer that agent H makes the investment since their utility values are higher, though this is not a necessary condition for the equilibrium.

We also see that incentives lead to lower CT testing thresholds: \(0.942 < 0.952\) (agent P) and \(0.542 < 0.738\) (agent R). The incentive sharing rates that maximize agent H’s utility are \(\alpha^{**} = 7.6\%\) for agent H and \(\beta^{**} = 36.5\%\) for agent R, leaving 55.9% to agent H. All three agents prefer the incentive scenario over the no incentive scenario as they experience utility gains, \(U^{**} - U^*,\) of 76 (agent H), 9 (agent P) and 21 (agent R).

In this numerical example, we had assumed that agents care about both monetary and patient health benefits \(\lambda^H = \lambda^P = \lambda^R = 10\). If agents only cared about health benefits, and not money, their threshold would be lower; \(\theta_P^{*} = 0.900 < 0.952\) and \(\theta_R^{*} = 0.500 < 0.738\), given CT scanner investment by agent H. Without investment, the health-maximizing testing thresholds reduce even further; \(\theta_P^{*} = 0.890 < 0.947\) and \(\theta_R^{*} = 0.450 < 0.700\). If agents only cared about money, their testing threshold would be 1.

Lastly, we perform a sensitivity analysis to investigate the circumstances under which agent H would change its investment decision (Table 3). We vary one model parameter at time to determine the transition point at which agent H would switch from investment \((a_1)\) to status quo \((a_2)\).

The results can be interpreted as follows. An increase in CT scanner investment cost \(k_1\) beyond the transition point leads to a no investment decision by agent H. Comparing the incentive with the no incentive scenario, we see that incentives make an investment

<table>
<thead>
<tr>
<th>Table 2 Equilibrium results of base case</th>
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<tr>
<td></td>
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<tr>
<td>No incentive</td>
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<tr>
<td>With incentive</td>
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<tr>
<td>No incentive</td>
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<tr>
<td>With incentive</td>
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<tr>
<td>Investment ((a_1))</td>
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<td>Status quo ((a_2))</td>
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<td>(\theta_P) Testing threshold by P</td>
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<td>0.952</td>
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<td>0.941</td>
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<td>(\theta_R) Testing threshold by R</td>
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<td>(U^R) R’s utility</td>
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Table 3 Sensitivity analysis of agent H’s optimal investment decision

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Parameter description</th>
<th>Initial value</th>
<th>Transition point</th>
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<tr>
<td>$k_1$</td>
<td>Investment cost</td>
<td>200</td>
<td>328</td>
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<td>$c^H(s_1)$</td>
<td>Maintenance cost</td>
<td>10</td>
<td>193</td>
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<td>$\gamma_c$</td>
<td>Cost impact from agent R on H</td>
<td>3</td>
<td>13.7</td>
</tr>
<tr>
<td>$\gamma_p$</td>
<td>Revenue impact from agent R on H</td>
<td>3.5</td>
<td>None</td>
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<tr>
<td>$\delta$</td>
<td>Diagnostic accuracy</td>
<td>0.05</td>
<td>0.031</td>
</tr>
<tr>
<td>Pr($s_1</td>
<td>a_1$)</td>
<td>Probability of high maintenance cost given the decision to invest</td>
<td>0.9</td>
</tr>
</tbody>
</table>

less attractive or likely, since 307 < 328. The same effect can be observed for maintenance costs, cost impact factor, and, in opposite direction, for diagnostic accuracy. For the other parameters in Table 3, no transition point existed in our numerical example. Additionally, the analysis showed that incentives reduce the attractiveness of a CT scanner investment for agent H; in other words, incentives reduce the CT scanner investment propensity of hospitals.

5.2 Optimal Incentive Distribution Mechanism: Effect of Cost Benchmark $M$

Next, we analyze the effect of the cost benchmark $M$, a key policy decision variable for CMS. We first analyze how $M$ affects agent H’s CT scanner investment decision. Figure 4 shows the change in agent H’s utility with respect to $M$ for the investment and status quo decision. Since the ACO receives higher incentives with a higher cost benchmark $M$, the utility for agent H, who retains a share of the overall incentive, increases. For the parameters of our numerical example, an investment is always the preferred choice. However, the difference in utility between investment and status quo gets smaller with increasing $M$. The health policy interpretation is that by providing higher incentives through less stringent cost benchmarks, CMS makes medical technology investments less attractive to hospitals.

While the investment decision remains the same for varying $M$, the incentive distribution within the ACO changes. In Figure 5, we can distinguish between three areas exhibiting different incentive distribution patterns.

- **Area a**: for small $M$, agent H gives the entire incentive to agents P and R, i.e., $\alpha + \beta = 1$.
- **Area b**: for intermediate $M$, agent H shares the incentive with agents P and R, i.e., $0 < \alpha + \beta < 1$.
- **Area c**: for large $M$, agent H keeps the entire incentive to itself, i.e., $\alpha = 0$, $\beta = 0$.

For small $M$ and thus low MSSP incentives for the ACO (area a), agent H chooses to pass on all incentives to agents P and R to induce the largest possible CT test reduction. In contrast, for a large $M$ and thus high MSSP incentives (area c), agent H benefits most from keeping the incentive entirely to itself. In area b, the incentive distribution lies between the two extremes.

In choosing $M$, CMS needs to provide incentives that result in a CT testing threshold that maximizes patient health. As shown previously, the health-maximizing CT test thresholds are $\theta^*_hP = 0.900$ and $\theta^*_hR = 0.500$. For $M = 3300$, the patients’ health-maximizing and agent P’s utility-maximizing CT testing threshold of $\theta^*_P = \theta^*_hP = 0.900$ is achieved; marked by a blue dot in Figure 5. Higher $M$ reduces the sharing percentage $\alpha^*$, and with it the CT testing threshold increases.

Higher incentives paradoxically result in more CT testing, but can be explained by the incentive re-distribution effect within the ACO. On the other end of the spectrum, too low incentives, $M < 3300$, result in insufficient testing, and are undesirable from a patient health...
perspective. Agent R’s testing threshold $\theta^*_{R}$ stays above the health-maximizing threshold of $\theta^*_{h} = 0.500$ over the entire range of $M$.

In choosing $M$, CMS also needs to consider the willingness of the ACO and its members to participate in the incentive program in the first place. For $M < 3600$, agent R’s utility is lower than in the no-incentive scenario. For $M < 3500$, agent P prefers the no-incentive scenario, and for agent H this transition occurs for $M < 3300$. The policy implication is that CMS may have to set a higher cost benchmark than desirable from a patient health or payer cost perspective to ensure agents’ participation in MSSP. If CMS merely had to convince agent H to participate, and agents P and R could not opt out, CMS should set $M$ slightly above 3300, which makes agent H just willing to participate.

Table 4 summarizes the system-wide costs, i.e., total billings, MSSP incentive, CMS’s net costs and patient health benefits. As just discussed, for $M = 3300$ the health benefit is maximized, and goes down for higher and lower $M$. With increasing $M$, the cost to CMS increases, but $M \geq 3600$ may be necessary to ensure the participation of all stakeholders.

Whether CMS prefers to even offer MSSP under these circumstances, depends on CMS’s willingness to pay for health, $\lambda_{CMS}$. Compared to the no incentive case, MSSP would improve the health of patients, even for a cost benchmark $M$ that is higher than the health maximizing value.

In summary, the policy implications for CMS are that the cost benchmark $M$ needs to be carefully chosen. Too much incentives, in the form of a too lenient cost benchmark, can paradoxically result in more CT testing. The patient health maximizing cost benchmark may not be feasible since agents would not participated in MSSP due to the more attractive fallback (no incentives). CMS would be advised to perform a detailed analysis before setting the cost benchmark. Giving into the demands of ACOs to raise the cost benchmark, would not only increase costs, but could result in lower quality of care.

6 Conclusion

In this paper, we developed a multi-level decision-making model with a hierarchical game structure, and evaluated the effects of MSSP on health care decision-making within the scope of radiology and ACOs. We used MSDT to capture the multi-level interactions and interdependencies of CMS, hospitals, primary care physicians, and radiologists. We modeled the agents’ responses to incentives while taking into account the influences across system levels.

We analyzed the model as a sequential game and solved it using the SPNE concept. Our analysis confirmed that in the scenario without incentive, i.e., an FFS system, both primary care physicians and radiologists are incentivized to order and perform excessive imaging tests. More importantly, we showed that the MSSP incentives can effectively decrease the CT testing thresholds, and can reduce hospitals’ propensity to purchase new CT imaging systems.

Using an illustrative numerical example, we derived additional health policy and decision insights for the stakeholders. If the cost benchmark set by CMS is too high, hospitals will keep all incentive to themselves. In this case, the MSSP has no effect on CT testing threshold reduction. When reducing the cost benchmark below a certain threshold, hospitals begin to share the incentive with physicians. The greater the sharing rate, the stronger the motivation by the physicians to reduce...
testing thresholds. Under certain conditions, the cost benchmark can be set just right so it reduces CT testing threshold to the patient health-maximizing threshold. Further reducing the cost benchmark can result in CT test underutilization. CMS also needs to consider the willingness of the ACO to participate in the program when setting the cost benchmark. A win-win-win-win situation for CMS, ACO, physicians and patients is possible with MSSP, but depends on many factors (model parameters).

Our analysis shows the importance of a model-driven and data-driven evaluation of MSSP, specifically when setting the cost benchmark. The current practice of ACOs negotiating for a more lenient cost benchmark may lead to higher costs and worse health outcomes. However, a too stringent cost benchmark can result in too low CT testing thresholds, and further may jeopardize the willingness of ACOs to participate.

The following limitations of our study should be considered. We assumed a single payer with a single incentive program, which over-simplifies the payment structures that both providers and payers experience in reality. Further, we assumed that health care agents seek to maximize their monetary payoffs and patients’ health benefits. In practice, agents care about a wider spectrum of attributes in their technology usage and investment decisions, such as malpractice litigation, patient preferences, hospital reputation, and budget constraint. Lastly, we analyzed a non-repeated game, without capturing the dynamic evolution of patient health and the temporal impact of incentives on health care costs and quality. Future work can address this limitation by modeling the patients’ disease progression using the multi-time-scale extension of MSDT [24,34,35]. Another important future research direction would be the calibration of this model with real-world data by empirically assessing the model parameters.

### References


### Table 4 CMS’s benchmarks, utility decompositions, and participation constraints

<table>
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<tr>
<th>M</th>
<th>Overall health care costs (Billings)</th>
<th>MSSP incentive</th>
<th>Net cost for CMS</th>
<th>Population health benefit</th>
<th>Agents’ willingness to participate in ACO as M increases</th>
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<td>3000</td>
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<td>R’s participation starts</td>
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</tr>
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</table>

Appendix

A1. Representation of agents’ UMPs

In agent P’s UMP, its monetary payoff is

$$\Pi^{P1}(\theta_P|a_h) = N_1 \cdot \left[ \frac{1}{2}(Ch_{A,N} + CS_{A,N}) - \theta_P \cdot \left[ CS_{A,N} - \tilde{q}_{SI,T} - (1 - \tilde{q})CS_{I,N} \right] \right] + \theta_P^2 \cdot \frac{1}{2} \left[ (CS_{A,N} - CH_{A,N}) + (1 - \tilde{q})(CH_{I,T} - CS_{I,N}) + \tilde{q}(CH_{I,N} - CS_{I,T}) \right].$$

Similarly, agent P’s health benefit is

$$B^{P1}(\theta_P|a_h) = N_1 \cdot \left[ \frac{1}{2}(\mu_{H,A,N} + \mu_{S,A,N}) - \theta_P \cdot \left[ (CS_{A,N} - \tilde{q}\mu_{S,L,T} - (1 - \tilde{q})\mu_{S,I,N} \right] \right] + \theta_P^2 \cdot \frac{1}{2} \left[ (CS_{A,N} - CH_{A,N}) + (1 - \tilde{q})(CH_{I,T} - CS_{I,N}) + \tilde{q}(CH_{I,N} - CS_{I,T}) \right].$$

In agent R’s UMP, its monetary payoff is

$$\Pi^{R1}(\theta_P) + \Pi^{R2}(\theta_R) = N_1 \cdot \theta_P \cdot c_1 + N_2 \cdot \theta_R \cdot c_1.$$

Agent R’s health benefit is

$$B^{R1}(\theta_R|a_h) = \left[ \frac{1}{2}N_2 \cdot \frac{1}{2}(\mu_{H,A,N} + \mu_{S,A,N})(2 - r) + \frac{1}{2}\mu_{S,A,N} \cdot r - \theta_R \cdot \left[ r \cdot (\mu_{S,A,N} - \tilde{q}\mu_{S,L,T} - (1 - \tilde{q})\mu_{S,I,N}) \right] + (1 - r)(\mu_{H,A,N} - \tilde{q}\mu_{H,I,N} - (1 - \tilde{q})\mu_{H,I,T}) \right] + \theta_R^2 \cdot \frac{1}{2} \left[ (\mu_{S,A,N} - \mu_{H,A,N}) + (1 - \tilde{q})(\mu_{H,I,T} - \mu_{S,I,T}) \right].$$
A2. Proof of Theorem 1

It is easy to obtain the expressions of $\theta_P^h$ and $\theta_R^h$ via taking derivatives of $B^P(\theta_P|a_k)$ and $B^R(\theta_R|a_k)$. Additionally, it is easy to check that $\theta_P^m = \theta_R^m = 1$.

Next, we show that $\theta_P^*$ satisfies $\theta_P^h < \theta_P^* \leq 1$. Denote

$$X_1 = \mu_{S,A,N} - \tilde{q}\mu_{S,I,T} - (1 - \tilde{q})\mu_{S,I,N},$$
$$X_2 = \mu_{S,A,N} - \mu_{H,A,N} + (1 - \tilde{q})(\mu_{H,I,T} - \mu_{S,I,N}) + \tilde{q}(\mu_{H,I,N} - \mu_{S,I,T}).$$

We have $0 < \theta_P^h = \frac{X_2}{X_1} < 1$, $X_1 < 0$, $X_2 > 0$. The first derivative of $U^P(\theta_P|a_k)$ with respect to $\theta_P$ is

$$\frac{\partial U^P(\theta_P|a_k)}{\partial \theta_P} = -N_1(\tilde{q}\mu_{S,I,N} + \lambda P \emptyset - \lambda P X_1) + N_1(1 - \tilde{q})((\mu_{H,I,T} - \mu_{S,I,N}) + \lambda P X_2).$$

Given the inequalities $c_{S,A,N} - \tilde{q}\mu_{S,I,T} - (1 - \tilde{q})\mu_{S,I,N} < 0$, $(1 - \tilde{q})(\mu_{H,I,T} - \mu_{S,I,N}) < 0$, $X_1 < 0$, $X_2 < 0$, we have

$$\theta_P^* = \begin{cases} c_{S,A,N} - \tilde{q}\mu_{H,I,T} - (1 - \tilde{q})\mu_{S,I,T} + \lambda P X_1, & \text{if } c_{S,A,N} - \tilde{q}\mu_{H,I,T} - (1 - \tilde{q})\mu_{S,I,N} + \lambda P X_1 > 0 < 1, \\ 1, & \text{if } c_{S,A,N} - \tilde{q}\mu_{H,I,T} - (1 - \tilde{q})\mu_{S,I,N} + \lambda P X_1 \geq 1. \end{cases}$$

Because $c_{S,A,N} - \tilde{q}\mu_{H,I,T} - (1 - \tilde{q})\mu_{S,I,N} - (1 - 2\tilde{q})(\mu_{H,I,T} - \mu_{S,I,N}) < 0$, the result $\theta_P^h < \theta_P^* \leq 1$ is then immediate.

Following the similar reasoning process as above, we have $\theta_R^h < \theta_R^* \leq 1$. □

A3. Proof of Theorem 2

For agent P: denote

$$X_3 = \mu_{S,A,N} - q\mu_{S,I,T} - (1 - q)\mu_{S,I,N},$$
$$X_4 = \mu_{S,A,N} - \mu_{H,A,N} + (1 - q)(\mu_{H,I,T} - \mu_{S,I,N}) + q(\mu_{H,I,N} - \mu_{S,I,T}),$$
$$X_5 = -\delta(\mu_{H,I,T} - \mu_{S,I,N}),$$
$$X_6 = -\delta(\mu_{H,I,T} - \mu_{S,I,N}) + \delta(\mu_{H,I,N} - \mu_{S,I,T}).$$

We have $\theta_P^h(a_2) = \frac{X_3}{X_4}$, $\theta_P^h(a_1) = \frac{X_3 + X_4}{2X_4}$. Notice that $X_3 < 0$, $X_4 < 0$, $X_3 > X_4$, $X_5 < X_6 < 0$, $X_5 < 0$, $X_6 < 0$, we have

$$\theta_P^h(a_1) - \theta_P^h(a_2) = \frac{X_4X_5 - X_3X_6}{(X_4 + X_6)X_4} > 0.$$

Therefore, when agent H switches from $a_2 = 1$ to $a_1 = 1$, $\theta_P^h$ increases.

Next we consider the changes in $\theta_P^*$ when agent H switches from $a_2 = 1$ to $a_1 = 1$. Denote

$$X_7 = \begin{pmatrix} c_{S,A,N} - (q + \delta)\mu_{S,I,T} - (1 - q - \delta)\mu_{S,I,N} + \lambda P [\mu_{S,A,N} - (q + \delta)\mu_{S,I,T} - (1 - q - \delta)\mu_{S,I,N}] \end{pmatrix}.$$
A4. Proof of Theorem 3

First, we provide the mathematical expressions for $\theta^*_p$ and $\theta^*_R$.

$$
\theta^*_p = \begin{cases} 
\tilde{\theta}_p, & \text{if } 0 < \tilde{\theta}_p < 1 \\
0, & \text{if } \tilde{\theta}_p \leq 0 \\
1, & \text{if } \tilde{\theta}_p \geq 1 
\end{cases}
$$

where

$$
\tilde{\theta}_p = \frac{\eta\alpha(1 + \gamma_p)c_1 + (1 - \eta\alpha)(c_{sA,n} - \tilde{q}c_{sI,T}) - (1 - \tilde{q})c_{sI,N}}{(1 - \eta\alpha)(1 - 2\tilde{q})c_{H,I,T} - c_{H,I,N} + \lambda^P[c_{sA,n} - \mu_{H,A,N} - \tilde{q}(\mu_{H,I,T} - \mu_{S,I,N})]} 
$$

$$
\theta^*_R = \begin{cases} 
\tilde{\theta}_R, & \text{if } 0 < \tilde{\theta}_R < 1 \\
0, & \text{if } \tilde{\theta}_R \leq 0 \\
1, & \text{if } \tilde{\theta}_R \geq 1 
\end{cases}
$$

where

$$
\tilde{\theta}_R = \frac{-c_1 + \eta\beta(1 + \gamma_p)c_1 + \lambda^R[r\cdot[c_{sA,n} - \tilde{q}c_{sI,T} - (1 - \tilde{q})c_{sI,N}] + (1 - r)[\mu_{H,A,N} - \tilde{q}(\mu_{H,I,T} - \mu_{S,I,N})]}{(1 - \eta\alpha)(1 - 2\tilde{q})c_{H,I,T} - c_{H,I,N} + \lambda^R[c_{sA,n} - \mu_{H,A,N} - \tilde{q}(\mu_{H,I,T} - \mu_{S,I,N})]} 
$$

Next, we prove Theorem 3(a). For agent P: denote

$$
X_{14} = c_{sA,n} - \tilde{q}c_{sI,T} - (1 - \tilde{q})c_{sI,N},
$$

$$
X_{15} = (1 - 2\tilde{q})c_{H,I,T} - c_{H,I,N},
$$

$$
X_{16} = \lambda^P[c_{sA,n} - \tilde{q}c_{sI,T} - (1 - \tilde{q})c_{sI,N}],
$$

$$
X_{17} = \lambda^P[c_{sA,n} - \tilde{q}c_{sI,T} - (1 - \tilde{q})c_{sI,N}],
$$

By Theorem 1, we have $X_{13} < X_{14} < 0$, $X_{16} < X_{15} < 0$. When $\theta_{p}^* \in (0, 1)$, we have

$$
\theta_{p}^* = \frac{\eta\alpha(1 + \gamma_p)c_1 + (1 - \eta\alpha)X_{13} + X_{15}}{(1 - \eta\alpha)X_{14} + X_{16}}.
$$

Take the first derivative of $\theta_{p}^*$ with respect to $\alpha$, and we have the inequality

$$
\frac{\partial \theta_{p}^*}{\partial \alpha} = \frac{X_{14}X_{15} - X_{13}X_{16} + (X_{14} + X_{16})(1 + \gamma_p)c_1}{(X_{14} + X_{16} - X_{17})^2} \eta < 0,
$$

$\eta \in (0, 1), \alpha \in [0, 1], \gamma_p \in \mathbb{R}^+.$

Hence $\theta_{p}^*$ is a strict decreasing function of $\alpha$ when $\theta_{p}^* \in (0, 1)$.

For agent R: similarly, when $\theta_{R}^* \in (0, 1)$, denote

$$
\theta_{R}^* = \frac{\eta(1 + \gamma_p)c_1 + (1 - \eta\alpha)X_{13} + X_{15}}{X_{18}}.$$

Take the first derivative of $\theta_{R}^*$ with respect to $\beta$, we have the inequality

$$
\frac{\partial \theta_{R}^*}{\partial \beta} = \frac{\eta(1 + \gamma_p)c_1}{X_{18}} < 0, \eta \in (0, 1), \beta \in [0, 1], \gamma_p \in \mathbb{R}^+.
$$

Hence $\theta_{R}^*$ is a strict decreasing function of $\beta$ when $\theta_{R}^* \in (0, 1)$.

Lastly, we prove Theorem 3(b). For agent P: using previous notations, we have

$$
\eta\alpha(1 + \gamma_p)c_1 + (1 - \eta\alpha)X_{13} + X_{15} \leq \frac{X_{13} + X_{15}}{X_{14} + X_{16}} (1 - \eta\alpha)X_{14} + X_{16},
$$

and the equality is reached when $\alpha = 0$ (by monotonicity).

Recall that $\theta_{p}^* = Min\{1, \frac{X_{13} + X_{15}}{X_{14} + X_{16}}\}$.

When $\frac{X_{13} + X_{15}}{X_{14} + X_{16}} \leq 1$, $\theta_{p}^* \leq \frac{X_{13} + X_{15}}{X_{14} + X_{16}} = \theta_{p}^*$. When $X_{13} + X_{15} > 1$, $\theta_{p}^* \leq 1 = \theta_{R}^*$.

Hence we always have $\theta_{p}^* \leq \theta_{R}^*$.

For agent R: following previous notations, we have

$$
\frac{-c_1 + \eta\beta(1 + \gamma_p)c_1 + X_{17}}{X_{18}} \leq \frac{-c_1 + X_{17}}{X_{18}},
$$
and the equality is reached when \( \beta = 0 \) (by monotonicity).

Recall that \( \theta_R^* = \min\{1, \frac{-c_I + X_{17}}{X_{18}}\} \).

When \( \frac{-c_I + X_{17}}{X_{18}} \leq 1 \), \( \theta_{R}^{**} \leq \frac{-c_I + X_{17}}{X_{18}} = \theta_{R}^{*} \).

When \( \frac{-c_I + X_{17}}{X_{18}} > 1 \), \( \theta_{R}^{**} \leq 1 = \theta_{R}^{*} \).

Hence we always have \( \theta_{R}^{**} \leq \theta_{R}^{*} \). \( \square \)

A5. Parameter Values for Numerical Analysis

The parameter values used in Section 5 Numerical Analysis are listed in Table 5.