

Modeling Multi-level Incentives in Health Care: A Multiscale Decision Theory Approach

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ABSTRACT

Financial incentives offered by payers to health care providers and patients have been identified as a key mechanism to lower costs while improving quality of care. How to effectively design incentive programs that can align the varying objectives of health care stakeholders, as well as predict programs' performance and stakeholders' decision response is an unresolved research challenge. The objective of this study is to establish a novel approach based on multiscale decision theory (MSDT) that can effectively model and efficiently analyze such incentive programs, and the complex health care system in general. The MSDT model captures the interdependencies of stakeholders, their decision processes, uncertainties, and how incentives impact decisions and outcomes at the payer, hospital, physician, and patient level.

In the first part of this thesis, we study the decision processes of agents pertaining to the investment and utilization of imaging technologies. We analyze the payer-hospital-physician relationships and later extend the model to include radiologist and patient as major stakeholders in the second part of this thesis. We focus on a specific incentive program, the Medicare Shared Savings Program (MSSP) for Accountable Care Organizations (ACOs). The multi-level interactions between agents are mathematically formulated as a sequential non-cooperative game. We derive the equilibrium solutions using the subgame perfect Nash equilibrium (SPNE) concept and the backward induction principle, and determine the conditions under which the MSSP incentive leads to the desired outcomes of cost reduction and quality of care improvements. In the third part of this thesis, we study the multi-level decision making in chronic disease management. We model and analyze patients' and physicians' decision processes as a general-sum stochastic game with perfect information and switching control structure. We incorporate the Health Belief Model (HBM) as the theoretical foundation to capture the behavioral aspect of agents. We analyze how incentives and interdependencies affect patients' engagement in health-promoting activities and physicians' delivery of primary care services. We show that a re-alignment of incentives can improve the effectiveness of chronic disease management.

Dedication

To my parents, who have supported me from the very beginning.

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Chapter 1

Introduction

1.1 Motivation

U.S. health care costs have been rising on average 6.0% per year over the past 20 years and constitute 17.4% of the nation's Gross Domestic Product [1]. Despite high expenditures, the U.S. health care system ranks last among 11 industrialized nations for a range of health care measures including quality, accessibility, and efficiency [2]. It is estimated that approximately a third or more of annual health care expenditures are unnecessary since they do not improve health outcomes for patients [3].

To curb costs and improve health care quality, policy makers and researchers have identified improvements in incentive structures as a key mechanism [4, 5]. Misaligned incentives can lead to decisions by hospitals, physicians, and patients that are costly and not necessarily beneficial to health outcomes. For example, in traditional fee-for-service (FFS) systems, individual health care providers such as physicians and radiologists are paid for each test or procedure they perform and are thus incentivized to do more, and more cost-intensive tests and treatments than if they were paid based on patient diagnoses or health outcomes [6]. Hospitals may invest in equipment and infrastructure that are profitable to them, but not

necessarily health or cost effective for patients and payers [7]. Meanwhile, insured patients may consume more health care than they would if they were to pay by themselves [8].

The investment and utilization of medical technologies is where misaligned incentives can cause significant problems. Medical technologies have been identified as one of the main health care cost drivers [9]. Technology-related expenses are estimated to account for 50% to 67% of the growth in U.S. health care spending [10, 11]. Technologies such as surgical robots and CT scanners have become indispensable treatment and diagnostic tools in modern patient care [12, 13]. However, advanced technologies are too frequently administered in cases where alternative and less expensive treatments and tests exist. For example, CT scans are frequently administered to diagnose appendicitis, even though an abdominal exam, blood work, and/or an ultrasound scan are similarly effective and cost less [14, 15, 16]. Other areas of CT scan overuse include chronic back pain and kidney cancer screening [17]. Unnecessary tests and treatments, in addition to being expensive, may also result in negative health outcomes, due to false positive diagnoses and harmful side effects, e.g., excessive radiation exposure [18, 19].

The Centers for Medicare and Medicaid Services (CMS), along with private insurers has been exploring and field-testing various payment innovations to reduce unnecessary and uneconomical care, such as the suboptimal investment and usage of medical technologies, with the goal of lowering health care cost while improving quality [20]. Such innovative payment models include pay-for-performance, shared savings, medical home, and bundled payments. Among them, a recently introduced and promising program by CMS is the Medicare Shared Savings Program (MSSP) with Accountable Care Organizations (ACOs) as major participants. An ACO is formed by a group of health care providers, typically hospitals and individual health care agents, who jointly coordinate the care of their patient population. In MSSP, ACOs continue to receive standard reimbursements for their Medicare patients, meanwhile receiving bundled financial incentives for cost reduction and meeting quality standards.

CMS has not provided any rules or guidelines for ACOs on how they should distribute the bundled incentives among ACO members [21]. Currently in practice, hospitals – who are typically the ACO leaders – propose and negotiate the incentive distribution mechanisms with their ACO partners. Each ACO is burdened with designing and negotiating their own internal incentive distribution program. Few guidelines exist and are mostly qualitative in nature. For example, DeCamp et al. [22] advocate for a “fair and equitable” approach, but specific insights or best practices have not yet been published.

Chronic disease management is another field where incentives need to be re-aligned. The prevalence and costly effects of chronic disease can often be prevented, delayed or mitigated by designing proper incentives for individual decision makers including physician and patient. For example, monetary incentives can enhance customers’ purchasing behavior of preventive and primary care services by reducing costs and/or increase disposable income. A reminder or suggestion from the provider can often trigger patients to adopt a healthy lifestyle that is beneficial for disease management. Meanwhile, physicians in practice focus mainly on acute care or chronic diseases that prompt a patient’s visit, instead of focusing on health maintenance issues [23]. Some major disincentives behind this problem are time constraints and poor reimbursement for activities such as counseling [23, 24]. How to incentivize physicians to optimally allocate clinical efforts and incentivize patients to proactively self-manage health, thereby improving health outcomes and reducing costs, is a question that needs to be addressed.

1.2 Research Objectives

The main objective of this work is to develop a multi-level decision-making model for the health care system, and to analyze and improve multi-level incentive mechanisms in health care to the benefit of patients, physicians, hospitals, and payers. One of the challenges in health care incentive design has been the lack of effective models that can capture the

complexities of the multi-level system and can provide decision support for stakeholders. In this research, we develop a novel modeling approach based on multiscale decision theory (MSDT) that can account for the interdependencies between stakeholders across system levels, support decision processes, and enable the re-design of incentive programs.

The following tasks are identified as the specific aims of this research.

1. Apply MSDT to model the multi-level system involving payers, hospitals, primary care physicians, specialists, and patients.

We model the decision processes of agents pertaining to the investment and utilization of imaging technologies, and pertaining to the engagement and delivery of chronic disease management activities. We apply and refine a graphical modeling approach to capture the relevant interdependencies between agents and to facilitate the mathematical model development. We begin by analyzing the payer-hospital-physician relationships and then extend the model to include radiologists. Later, we incorporate the temporal component and formulate the multi-level, multi-period interactions between physician and patient.

2. Design and evaluate the incentive mechanisms based on the decisions and outcomes of agents.

Based on the MSDT model, we evaluate the influence of MSSP incentives on the imaging technology investment decision and imaging ordering decisions, as well as on the outcome at each system level. We discuss how to optimally design the incentive distribution mechanisms of ACOs, considering the decisions of agents who maximize their individual goals. We also analyze how health care payers, at the top level of the hierarchical game structure, should design MSSP incentive policies. Furthermore, we discuss the incentive drivers for physicians to optimally allocate clinical efforts and for patients to proactively self-manage health. We focus on the interdependencies between physicians' and patients' actions and outcomes, and on intrinsic and extrinsic, financial and nonfinancial factors that influence agents' decisions in chronic disease management.

3. Analyze agents' decision-making in a game-theoretic setting.

For Chapter 3 and 4, the multi-level interactions between agents are mathematically formu-

lated as hierarchical and non-cooperative games. The mathematical formulation and solution technique relies on MSDT and incorporates methods from cost-effectiveness analysis, operations research, as well as normative and behavioral decision theory, including game theory. We derive the equilibrium solutions using the subgame perfect Nash equilibrium (SPNE) concept and the backward induction principle. For Chapter 5, we use stochastic games with switching control and perfect information to model patients' and physicians' decision processes. Further, we incorporate the Health Belief Model (HBM) as our basis for modeling the behavioral aspect of patients and physicians. A nonlinear programming approach is used to solve the game.

1.3 Organization of the Thesis

This introduction is followed by Chapter 2, which gives an overview on the relevant literature. We present related work on multiscale decision theory, health care agent interactions and incentives modeling, ACOs and MSSP, diagnostic imaging decision process, medical technology investment decision process, stochastic games, stochastic models in chronic disease management, and Health Belief Model.

Chapter 3 introduces a preliminary model for the multi-level health care system involving payers, hospitals, and physicians. It begins with an introduction of research themes and model preliminaries. Next, we elaborate on the detailed model formulation and the detailed graphical representation. Finally, we present the analysis and numerical results.

Chapter 4 extends the multi-level model to include radiologists and patients as major stakeholders. It begins with research themes and model preliminaries, followed by the detailed model formulation and the graphical representation. Later, we present the analytical solutions and numerical analysis. We compare the scenario with and without incentives, and discuss the optimal incentive distribution mechanism.

Chapter 5 focuses on the chronic disease management problem and gives the multi-level,

multi-period decision-making model between physician and patient. It begins with the motivation and problem description, followed by the detailed model and algorithm. Next we present a case study and conduct the analysis on patient incentives and physician incentives. Lastly, we discuss the managerial insights from our model and give conclusions.

Chapter 2

Background and Literature Review

In this chapter, we review the relevant literature that is associated with this research. We begin by giving an overview on the multiscale decision theory, which is the main methodology we use in modeling. The second part reviews the related work on health care agent interactions modeling as well as the incentive mechanism design in health care. Next, we review health care literature with a focus on the key concepts relevant to our work, including ACOs and MSSP, diagnostic imaging ordering, and medical technology investment. Lastly, we discuss the relevant literature in Chapter 5, namely stochastic games, stochastic models in chronic disease management, and Health Belief Model.

2.1 Multiscale Decision Theory

MSDT is an approach in operations research that models and analyzes dynamic, multi-level systems with interdependent agents and hierarchical and stochastic decision-making networks. It accounts for interactions between agents, uncertainties between decisions and outcomes, and agents' strategic thinking through explicit modeling, and solves multiscale challenges across organizational hierarchies, time, space, and size [25].

MSDT builds upon concepts from distributed decision making [26], the theory of hierarchical, multi-level systems [27], and multi-agent influence diagrams, in particular dependency graphs [28]. It applies modeling and solution techniques from Markov decision processes [29] and stochastic game theory [30].

MSDT also provides a graphical modeling tool to decompose a complex system into multiple levels containing key stakeholders, and capture their decisions, outcomes, and interdependencies. Graphical models for agent interactions have been widely used by computer scientists and build upon decision analysis and probability theory. In MSDT, the *dependency graph* serves as a modeling aid to derive a mathematical formulation of the multiscale system, as well as a communication tool bridging the mathematical model with the real-world application.

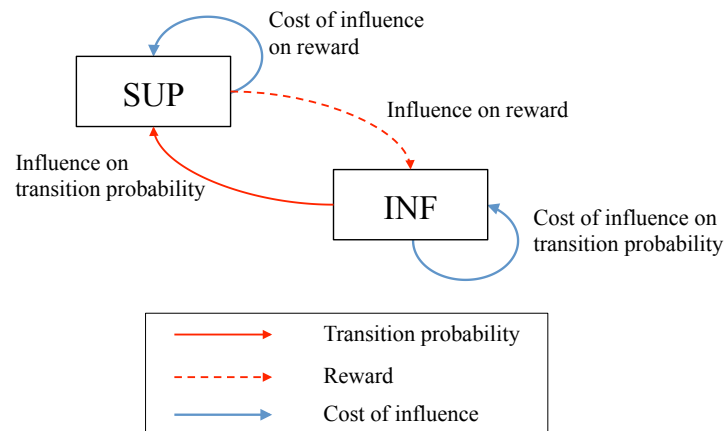


Figure 2.1: Dependency graph and notation

Figure 2.1 is a dependency graph that shows a prototypical two-agent MSDT model [25]. Two agents, represented by supremal (SUP) and infimal (INF), are faced with a decision-making problem. Depending on the decision chosen, the agent will transition to a state with transition probability and receive a reward associated with each state. Two agents affect each other through the state they transition to. Agent INF influences the transition probabilities of agent SUP (represented by the solid arrow), whereas agent SUP can choose

to give agent INF an incentive (represented by the dashed arrow). In the scenario where conflictive incentives can be seen between the two agents, incentives can motivate agent INF to take action in order to support agent SUP, given the right influence and incentive structure.

The theoretical foundations of multiscale decision theory were developed by Wernz [25]. In his dissertation, the basic two-agent interaction was considered, and the MSDT approach was established. The horizontal extension (multiple agents), the vertical extensions (multiple levels), and temporal effects (multi-time-scale) were also discussed. Following that, Wernz and Deshmukh [31] provided a more comprehensive discussion on the multi-organizational-scale and multi-time-scale MSDT modeling. A 3-agent, 3-period problem was explored, and effective and efficient solution algorithms were developed. Results as analytical equations can often be derived with low computational effort.

From the application's perspective, MSDT has been applied to a variety of multiscale systems. For example, a prototypical hierarchical relationship exists between a production planner and a material buyer in a manufacturing system. The material buyer's decision can affect the production planner's interests, whereas these two decision-makers are confronted with conflictive objectives in the game-theoretic situation. Reward mechanism could be designed such that the interests of the two agents are realigned [32, 33, 34]. Wernz and Deshmukh [35] also discussed a more general setting in organizational design, where a supremal unit can motivate the infimal unit to increase its chance of success through rewarding the infimal unit a share of supremal unit's reward. Later, various service systems were also modeled and analyzed using MSDT, including customer service organization [36], maintenance service organization [37], and supply chain management [38]. However, no prior MSDT work has focused on health care, and modeling the multi-level health care system using MSDT remains a field that needs to be explored.

2.2 Models for Health Care Agent Interactions and Incentives

There are two major streams of research that analyze health care payment models and incentives: (1) analytical model based on principal-agent theory and (2) simulations. The principal-agent problem describes a dilemma where the agent's decision(s) can impact the principal's interests, while the agent makes decision based on its own best interests instead of the principal's. Such situations are often coupled with hierarchical interactions, incomplete and asymmetric information. Common examples of the principal-agent dilemma include investor (principal) and fund manager [39], voters (principal) and politicians (agent) [40], and stakeholders (principal) and organizational management (agent) [41]. In health care, the principal-agent dilemma can be found in a number of interactions between health care system stakeholders. For example, insured patients (agent) often consume more health care services than non-insured patients do, leading to higher cost for their insurance companies (principal); physicians (agent) sometimes prescribe tests or procedures that may not be truly necessary for the clinical case of patient (principal), in order to get additional financial reward.

Agency theory proposes mechanism to overcome principal-agent problems and has originally been developed and applied to aforementioned challenges in economics [42], politics [43], and firms [44]. In health care, agency theory has been used to model agent behavior and to develop mechanisms, such as incentive payments or contracts, that can resolve moral hazard and conflicting objectives, and align actions by stakeholders [45]. For example, in effective incentive mechanism design, the payer (principal) – typically an insurance company or the government, in case of a single payer system – seeks to identify a reimbursement agreement with the provider (agent), e.g., physician or hospital, that motivates high-quality and cost-effective patient care.

In the domain of agency theory in health care, Fuloria and Zenios [46] developed a dynamic

principal-agent model with which they evaluated an outcome-adjusted reimbursement system consisting of prospective payments and quality-based retrospective adjustments. Building upon this model, Lee and Zenios [47] conducted an empirical study in which they analyzed data from Medicare's end-stage renal disease program. Their findings documented the effectiveness of the outcome-adjusted reimbursement system. Yaesoubi [48] formulated a principal-agent model for preventive medical care. Payers and providers design and choose contracts that optimize their objectives, while also maximizing the welfare of patients. Boadway et al. [49] considered a problem setting where managers and physicians are responsible for different decisions within the hospital under the effect of the diagnosis-related group (DRG) and FFS reimbursements. Principal-agent models not only apply to the interactions between payer and provider, but also to interactions with patients. For example, Pope et al. [50] proposed multilateral contracts between payers, providers and patients and showed under which conditions these are superior to bilateral agreements in terms of cost and quality of care.

Most literature on principal agent theory and its application on health care systems considers two-level hierarchies, or at most three-level hierarchies. A comprehensive and general multi-level framework that incorporates all levels, including policy makers, payers, hospitals, physicians and patients, has not yet been developed, and the mathematical tractability of principal-agent models with more than two levels remains a challenge. Furthermore, most principal-agent models that focus on incentive payments or contracts often simplify or exclude the clinical decision processes of health care agents; hence the decision support for agents such as service providers is limited by research scope.

Another stream of research focuses on analyzing payment models and incentives using simulations. Montreuil et al. [51] used agent-based modeling and simulation in distributed health care delivery systems and presented a generic conceptual framework based on a three-level categorization of the major simulation components. Later, Charfeddine and Montreuil [52] illustrated the simulation framework through a chronic disease population and health care delivery network example, showing that the demand for health care services and the orga-

nization and functioning of the delivery network can be adequately simulated. Bigus and Sorrentino [53] developed a simulation framework that includes payers, providers and patients to analyze the effect of incentives in evidence-based health care. Basole et al. [54] designed and developed an organizational simulation model to examine the effectiveness of different health care management strategies and to address the tradeoffs between health outcomes and health care costs.

A special class of simulation is system dynamics (SD) that captures the dynamic behavior of complex systems by focusing on stocks and flows, feedback loops, and delays [55]. Rauner and Schaffhauser-Linzatti [56] presented a strategic SD model that analyzed the impact of a new performance-based reimbursement system of inpatients in Austria and identified hospitals' reimbursement maximization strategies. Ng et al. [57] developed a SD model to study the affordability and accessibility of health care systems. Particularly, they compared four macro policies, such as financial subsidies and GDP budget assignment, in improving health care affordability in Singapore. Meker and Barlas [58] investigated the dynamic impacts of pay for performance system on the behaviors of hospitals and physicians, focusing on physician-patient interactions, revenue pressures, health outputs and quality.

Simulation models are well suited to model complex systems and investigate emergent phenomena. However, structural insights may not be readily available, and obtaining results often requires extensive computational studies.

2.3 ACOs and MSSP

CMS established MSSP to facilitate the coordination among health care providers and to improve the quality of care for Medicare beneficiaries and contain the rising costs. The major participants of MSSP are ACOs. An ACO is formed by a group of health care providers, including hospitals, physicians, and other individual health care providers, who jointly coordinate the care of their Medicare patient population. Initiated by the Patient

Protection and Affordable Care Act of 2010, MSSP with the first ACOs were launched in 2012. As of May 2014, 338 MSSP ACOs were serving 4.9 million patients and have achieved net savings of \$417 million at improved levels of care quality [59, 60]. As projected by the U.S. Health and Human Services Department, by 2016, 85% of all traditional Medicare payments will be tied to quality or value through programs such as MSSP [61].

Under MSSP, ACOs continue to receive standard reimbursements for their Medicare patients. That means individual providers like physicians and radiologists are paid on a FFS basis, and hospitals receive prospective payments according to DRG for the inpatient sector and according to the Outpatient Prospective Payment System (OPPS) for the outpatient sector.

Moreover, if an ACO meets quality standards and also achieves savings that meet or exceed a Minimum Savings Rate (MSR) set by CMS based on national averages, the ACO will receive a certain share of the net savings, which is determined by comparing the average per capita benchmark set by CMS to the ACO's actual average per capita expenditures. ACO shares all the savings up to a performance payment limit. ACO could also optionally share losses, if any, up to a loss-sharing limit. ACOs can choose between two types of MSSP models: (1) one-sided model that allows shared savings but not shared losses, and (2) two-sided model that requires ACOs to share both the savings and losses. For the one-sided model with only saving-sharing, up to 50% of savings are available. For the two-sided model with both saving-sharing and loss-sharing, up to 60% of savings are available, but ACOs would have to pay 40%-60% of the cost difference as a penalty should they exceed CMS's cost benchmark [62]. Additionally, CMS recently proposed new regulations and introduced a track 3 plan that encourages ACOs to take on greater performance based risks. The track 3 plan proposes a higher sharing rate of 75%, while increasing the shared losses to up to 75% [63].

Early discussions on the concept of MSSP and ACO can be found in Fisher et al. [64]. Building upon their work, Lowell and Bertko [65], Greaney [66], Shortell et al. [67], Shields et al. [68], and Fisher and Shortell [69] further analyzed ACO concept and their key features, including local accountability, shared savings and performance measurement. Ginsburg [70]

and Berwick [71] explored the relationship between MSSP and ACOs. McClellan et al. [72] proposed the national strategies to put ACO into practice and to address the barriers to effective implementation of accountable care.

Literature also summarized five major types of ACO organizational structures, including multispecialty group practice, hospital medical staff organization, physician-hospital organization, interdependent practice organization, and health plan-provider organization or network [73, 74]. Devers [75] identified the key characteristics of each ACO model and made a comparison of them by provider types. These prior studies are mostly qualitative and focus on macro-level health care policies. Few quantitative studies or mathematical models have been developed that analyze and predict the effects of MSSP incentives on stakeholder behavior and financial and health outcomes. One notable exception is the work by Pope and Kautter [76], where the authors developed a mathematical model and applied simulated data to determine minimum savings requirements in shared savings payment structures. The paper considered the interaction between payer and ACO, but did not model the interactions among ACO members.

2.4 Imaging Ordering Decisions

Researchers have implemented various approaches to model and analyze the decision process of using imaging tests. Pauker and Kassirer [77, 78] were the first to derive mathematical expressions for testing and test-treatment threshold to guide clinical decision-making. Specifically, a “testing” threshold refers to the indifference point where the value of withholding treatment is equal to the value of performing the diagnostic test; and a “test-treatment” threshold refers to the indifference point where the value of performing the diagnostic test is equal to the value of performing treatment. Derivations of these thresholds were based on data that reflects the risks and benefits of treatment as well as the risks and reliabilities of diagnostic tests.

Eventually, physicians can decide the best course of action by comparing the estimated probability of disease of a patient with the two calculated thresholds. In other words, a testing threshold is the probability of disease above which a diagnostic test should be performed and below which the likelihood of the diagnosis is too low to justify the test. A test-treatment threshold is the probability of disease above which treatment should be initiated without any testing.

The aforementioned studies considered the medical decision making and the associated test and test-treatment threshold in a normative fashion. In contrast, Eisenberg and Hershey [79] derived the thresholds in a descriptive fashion, by estimating the probabilities of disease at which physicians order a diagnostic test or perform treatment without testing. The ranges of the two threshold values were empirically calculated.

With a focus on clinical practice, Swets et al. [80] proposed a general protocol for diagnostic technology evaluation by measuring diagnostic sensitivity and specificity and generating a relative operating characteristic (ROC) curve for each imaging technology. Based on that, Sox [81] incorporated Bayes' theorem into modeling diagnostic uncertainty, and distinguished and calculated the post-test and pre-test probability of disease of patients. The paper also discussed the pitfalls in estimating probability and the limitations of the use of sensitivity and specificity of diagnostic tests. Yaesoubi [48] modified the concept of thresholds and derived the indifference point of withholding and performing preventive intervention using Quality-Adjusted Life Year (QALY) measures. Instead of using probability of disease, the concept of *patient rank* was used to capture the heterogeneous patient pool and to interpret the different expected magnitude of devastation due to the disease. Doubilet [82] considered the scenarios where two or more tests are available to choose and the discrete test has two or more values (non-binary test), and proposed a mathematical approach to assist the diagnostic test decision-making.

Phelps and Mushlin [83] extended the scope of clinical decision analysis beyond the characterization of ROC curves by considering costs of therapy and testing. A cost-effective

analysis in combination with a decision tree was used to evaluate new diagnostic medical technologies. Two decision-making situations were considered: (1) constant incremental benefits of tests across patient population no matter what fraction of the population receives the tests; and (2) declining benefits of tests as the number of procedures expands.

2.5 Medical Technology Investment Decisions

In Chapter 3 and 4, we model a hospital's decision regarding the investment of a new and more advanced medical technology equipment. From a normative perspective, a technology investment decision is a typical decision-making problem that is comprised of decision makers, decision objectives and decision alternatives [84]. Decision makers can be individuals or a group, which receive information from other stakeholders in the organization. The decision objectives should be derived from the organization's mission. Decision alternatives represent discrete investment options. In our model, we consider the binary decision of investing or not investing in one type of medical technology equipment.

Hospitals have multiple organizational objectives when making these types of capital investment decisions. Previous research has identified three main objectives: technology leadership, profitability, and value for patient and community [85, 86, 87]. Wernz et al. [88] conducted an international study and found that financial, quality and strategic considerations inform the decision process in most hospitals. Additional considerations are budget constraints, competition and request from physicians. In our model, we consider financials and health outcome, with the latter being a proxy for quality and technology leadership.

In normative decision theory, mathematical optimization approaches are used to identify best investment alternatives, e.g., the simple multi-attribute rating technique [89], goal programming [90, 91], cost-effectiveness analysis [92, 93], real options analysis [94, 95], game theory [96], and multi-objective optimization [97].

Keown and Martin [90] used the zero-one goal programming method to address the multiple

conflicting goals and indivisibility of projects in the decision environment of hospital administrators. Wacht and Whitford [91] implemented a similar goal programming approach in hospital capital budgeting and meanwhile presented the institutional characteristics of non-profit hospitals, which can prevent successful application of conventional efficiency-oriented models. Focke and Stummer [97] used the multi-objective programming approach to determine the solution space of all portfolios of medical technology investments, and then proposed a decision support tool that assists budget planning committees in the interactive exploration of the solution space, until a satisfying portfolio is jointly reached.

Cost-effectiveness analysis (CEA) is an economic analysis that compares costs and outcomes among multiple actions. In hospitals' medical technology investment, the magnitude of the incremental net benefit of a technology can be economically evaluated, based on clinical effectiveness, quality of life and costs; and technology alternatives are often compared using CEA measures, e.g. QALYs [92, 93].

Real option analysis (ROA) allows hospitals to incorporate option values into the economic evaluation of a specific technology and compare multiple alternatives. ROA is especially beneficial for the evaluation of equipment that requires substantial capital outlay, while evidence is insufficient and uncertainties are involved [94, 95].

Levaggi et al. [96] considered the interactions between three actors, a purchaser, a hospital, and a representative physician, and discussed a game-theoretic scenario where the presence of devoted physicians enhances the general level of medical quality and thus allows the hospital to reduce its medical technology investment.

However, none of these mathematical approaches has considered how investment and usage decisions affect each other, and how both of these in turn are affected by health care incentives. In this research, we analyze these interdependencies.

2.6 Stochastic Games

Stochastic games, also known as competitive Markov decision processes, describes decision making situations where outcomes are partly random and partly controlled by two or more decision makers. As a class in game theory first introduced by Shapley [98], stochastic games combines the concepts of Markov process and dynamic programming with those of matrix game. Conventional normal form games are represented by way of a matrix, where players simultaneously and independently choose an action. The reward of each player depends solely and deterministically on the actions players have chosen. Stochastic games can be viewed as a collection of matrix games, where the transitions among these games depend on the current state and on the actions chosen at each stage [99]. It can be also viewed as generalized Markov decision process (MDP) that two or more players control the stochastic processes.

Stochastic games has been referred to in a wide spectrum of research contexts, such as dynamic games, differential games, state-space games, sequential games, and Markov games [100]. Due to the complexity of the nature of the games and the searching for equilibrium solutions, the application of stochastic games is often limited to highly structured and relatively aggregated models, such as models with certain data structures. Among them, Filar and Vrieze [30] identified several economic model prototypes where stochastic games are applicable, such as strike negotiation, pollution tax, the inspection problem, the presidency game, etc. Huang and Krishnamurthy [101] formulated the transmission rate adaptation in cognitive radio networks as a stochastic game with switching control structure. Lye and Wing [102] modeled the interactions between an attacker and an administrator in the network security domain as a general-sum stochastic game and found multiple equilibria solutions. Reinganum considered industrial R&D process as a continuous-time stochastic patent race and developed the optimal resource allocation strategies for competing firms. Stochastic games has also been applied to other disciplines including military operations [103], sports

strategy [104], and natural resource management [105].

2.7 Stochastic Models in Chronic Disease Management

In the field of chronic disease management in healthcare, MDP has been widely used to model the evolution of patient health status. MDP considers the patient disease progression as an uncertain process, and that the transition probabilities depend not only on the nature of the disease but also on clinical intervention. An overview of MDP and its application on medical treatment decisions can be found in Schaefer et al. [106]. Alagoz et al. [107] formulated the organ transplantation problem for end-stage liver disease patients as a MDP model. The optimal control-limit policy was proposed that divides the patient health state space into two regions. This study was further extended in Alagoz et al. [108], where a double-control-limit policy was proposed that divides the state space into three regions. Maillart et al. [109] used partially observed MDP to capture the age-based dynamics of breast cancer risks and identified efficient screening policies. Hey and Patel [110] considered two types of healthcare consumptions with (1) preventions that prevent the probabilistic transitioning to an adverse *sickness* state and (2) acute care that expedites probabilistic transitioning to a beneficial *health* state, and modeled the disease management problem as a MDP with budget constraint.

One common limitation of the prior studies is that they assumed a single decision maker, either provider, patient or payer, that takes the complete responsibility of chronic disease management. In reality, however, chronic disease management is a joint effort by both physicians and patients, and its outcome relies heavily on the decisions of both parties as well as on the underlying incentive system that affects individual choices [111]. Chapter 5 of this thesis is the first, to our best knowledge, to model the chronic disease management problem as a two-player stochastic game. We use a game-theoretic method to account for the interactions between a physician and a patient and to analyze how incentives influence

each player in the game.

2.8 Health Belief Model

HBM was developed in the early 1950s by social scientists in the U.S. Public Health Service to explain the failure of people adopting disease prevention strategies for early detection of disease [112]. It has been widely applied to understand patients' behavior, e.g., patients' responses to symptoms and compliance with medical treatments [112], as well as to explain the behavioral aspects in non-healthcare domains, such as users' computer security behavior [113] and financial transaction security behavior [114]. HBM identified six main constructs that influence people's decisions about whether to take actions to prevent, screen for, and control illness. The six constructs together with their causal relationships are shown in the following figure [115].

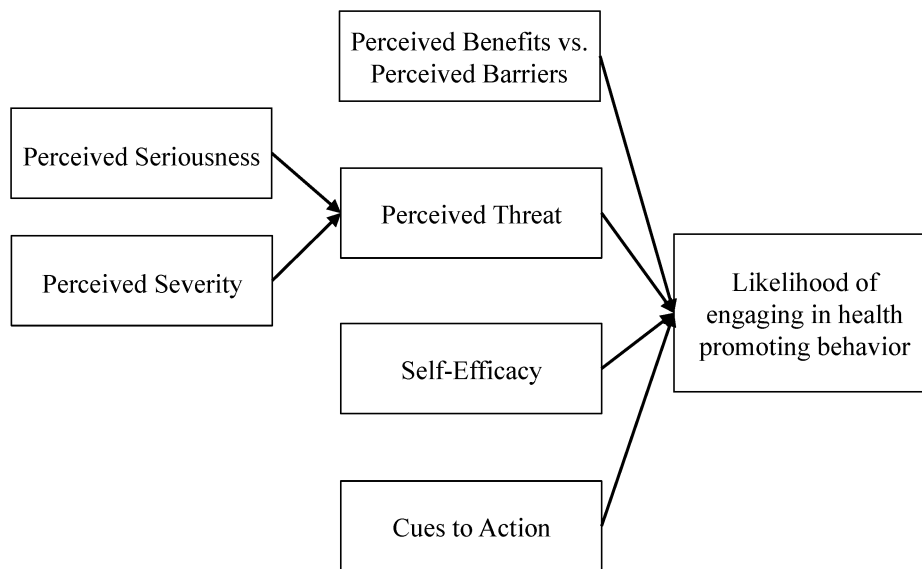


Figure 2.2: The Health Belief Model illustration

Despite the massive discussions of HBM theoretical framework, one significant drawback of this theory is the lack of strategic recommendation capability for changing health-related actions [112]. In our study, we incorporate HBM and its six major influencers into model-

ing primary care physician’s and patient’s decision processes of chronic care management. Specifically, perceived susceptibility is the belief about the chances of getting a condition, and is depicted using health status transition probabilities in our model. Perceived severity is the belief about the seriousness of a condition and its consequences, and is described using health utilities associated with different health status. Perceived benefits is the perceived effectiveness of taking actions to reduce risks or seriousness, and is a combination of primary care effect, acute care effect, and the lifestyle effect in our model. Perceived barriers are beliefs about the material and psychological costs of taking actions, and they are defined as different types of cost functions. Self-efficacy is the confidence and ability in one’s ability to take action; similar to perceived barriers, we use psychological costs to represent this construct. Last but not least, cues to action are the exogenous factors that activate patient’s “readiness to change”, and they are illustrated by assuming physicians can trigger patients to change lifestyles in our model [116].

HBM is our theoretical basis for modeling behavioral decision-making aspect while stochastic games accounts for the normative decision-making aspect. With the integration of these two methodologies, we aim to identify optimal strategies for providing and engaging in health-promoting activities in a quantitative fashion.

Chapter 3

How Shared Savings Incentives Affect Medical Technology Use and Investments

In this chapter, we provide the preliminary multi-level decision-making model consisting of three hierarchies (payer, hospital, and physicians). We begin by introducing our research themes, motivating example, and model preliminaries. Thereafter, we elaborate on the detailed mathematical formulation, followed by the analysis and numerical results.

3.1 Research Themes and Preliminaries

3.1.1 Motivating Example

This work is primarily motivated by the influential role of payment schemes and incentive structures in curbing costs and improving health care quality as identified by policy makers and researchers, with a focus on the usage and investment of medical technologies. The avail-

ability and utilization of medical technologies is largely determined by health care providers, including hospitals, physicians, etc. Their investment and usage decisions are influenced by the reimbursement modalities and associated incentives [49, 117].

CT scan is chosen as an exemplary medical technology. Like many other medical technologies, constant technological advances in CT scan technology push hospitals to upgrade their equipment. Meanwhile, CT scans are overused by health care providers in the U.S. [14, 15, 16]. For many patients, the necessity of a CT test is not well justified, and less expensive alternatives, e.g., ultrasound or wait-and-see, exist. Furthermore, the care provided in the radiology department can be affected by multiple parties and factors. For example, the purchase of CT scanners affects hospitals' cost and quality, as well as the imaging ordering behavior of physicians.

The aforementioned suboptimal investment and utilization of CT technologies and the fragmentations among health care agents can be rectified in part by payment and care coordination models. The innovative payment model we choose is MSSP for ACOs. Under MSSP, ACO members receive shared savings incentive in addition to conventional Medicare payments. Table 3.1 lists the general payment policy associated with the service types for each provider. In this model, we choose the inpatient sector, where hospitals receive DRG payment and physicians, who are assumed to be free agents and partner with hospitals and jointly form an ACO, are reimbursed on a FFS basis.

MSSP entails that if the cost of care of an ACO is below the CMS cost benchmark and the quality standards are met, the ACO will receive 50-60% of the cost savings from CMS [62]. CMS does not regulate or provide guidance on the distribution of shared savings after ACOs receive them. An ACO needs to decide how to distribute this payback among its members. The incentive distribution, together with the aforementioned interdependencies in the system, affect agents' decisions and outcomes in different ways, and make designing incentive mechanisms even more complex.

Table 3.1: General Medicare payment policy

Provider	Service Type	Medicare Payment	General Payment Policy
Hospital	Inpatient	Part A	Diagnosis Related Group (DRG)
	Outpatient	Part B	Outpatient Prospective Payment System (OPPS)
Physicians/radiologists (free-agent)	Inpatient	Part B	Payment is based on a fee schedule (FFS)
	Outpatient		
Physicians/radiologists (employed)	Inpatient	N/A	Payment is based on hospital contract, e.g., salary
	Outpatient		

3.1.2 Model Overview and Preliminaries

To address and overcome the complexities of health care system, we build upon a *multi-level system perspective* first proposed by Ferlie and Shortell [118] and later adopted by the Institute of Medicine and the National Academy of Engineering in a joint report [119]. In Figure 3.1, the health care system is categorized into four levels, each of which contains numerous stakeholders, affecting each other within and across system levels.

In this research, we use MSDT to formulate an analytical model that captures the interactions and interdependencies among multiple health care agents, including payers, hospitals, and physicians. Our model and analysis focus on MSSP incentives and its effect on decisions by health care agents, in particular the decisions of CT scan investment and usage, as well as financial and health outcomes. Further, the model evaluates and optimizes incentive distribution mechanism among ACO members, including hospitals and physicians.

To support the model building process, we implement the *agent interdependence diagrams*, which can graphically capture and map the interdependencies of decisions and outcomes among agents. Figure 3.2 shows the agent interdependence diagram of the problem studied in this research. Agent interdependence diagrams use different types of arrows to represent

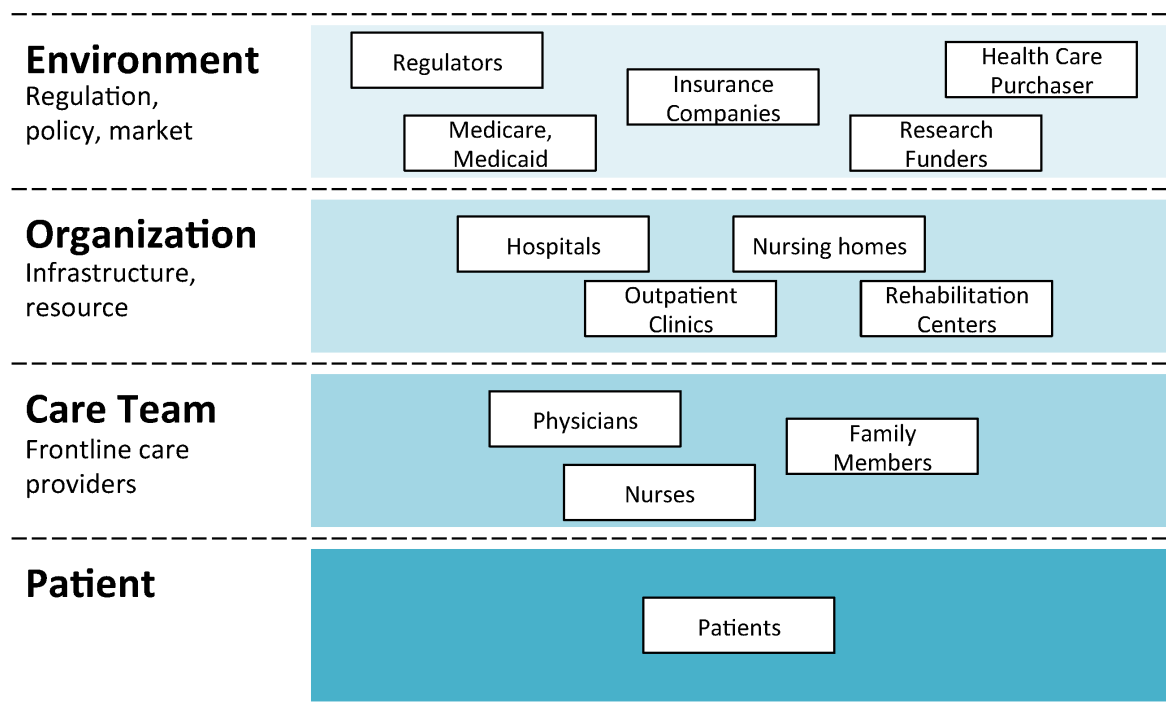


Figure 3.1: A multi-level system perspective on health care

the different interdependencies among agents. The dashed arrow represents a payment or an incentive, while the solid arrow represents other influences that affect decisions or outcomes. The letters D (decision) and O (outcome) at the beginning and end of an arrow indicate whether a decision or an outcome is affecting another agent's decision or outcome.

At the highest level of the system, the payer (here CMS) decides how to reimburse and incentivize ACOs via MSSP. Under MSSP, physicians are paid on a FFS basis, and hospitals receive payments according to DRGs, a fixed payment determined by the medical diagnosis of the patient. Additionally, ACOs receive a certain share $\mu \in [0,1]$ of the difference between their Medicare billings and cost benchmark $M \in \mathbb{R}_+$, both of which are decided by the payer. Medicare billings above the benchmark result in a penalty (negative incentive); Medicare billings below the benchmark result in a reward (positive incentive).

At the next lower, second level of the system, the hospital, referred to as agent H, makes

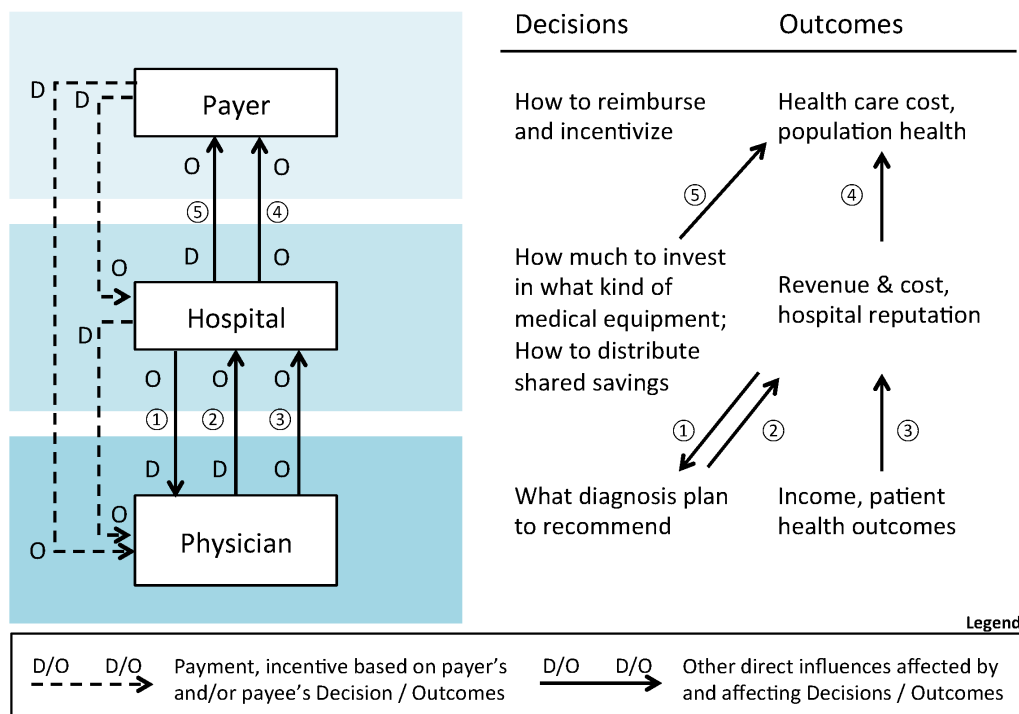


Figure 3.2: Agent interdependence diagram

two types of decisions, taking into account the payer’s incentive mechanism: (1) to buy a new, more advanced CT scanner, or not to buy a new device (status quo), and (2) what constant share $\mu \in [0,1]$ of the payer’s bundled incentive to give to the physicians (retaining share $1 - m$ for itself). We assume that agent H, as the ACO leader, can unilaterally decide this sharing percentage.

At the third and lowest level of the system, and after the decisions of the payer and agent H, the physician chooses the diagnostic intervention to recommend to a patient, i.e., whether to perform a CT scan or not. We assume that a patient follows a physician’s recommendation. We represent all physicians as a single agent P and consider their aggregate decision behavior. The aggregate decision of agent P is expressed as the share of patients who receive a CT scan, referred to as CT scan rate $a^P \in [0,1]$.

The sequential decisions of the three agents lead to a game-theoretic situation. Figure 3.3 summarizes the agents’ decisions and their sequence. We assume the overall structure of the

payer's incentive program has been set, but that the cost benchmark M still needs to be decided.

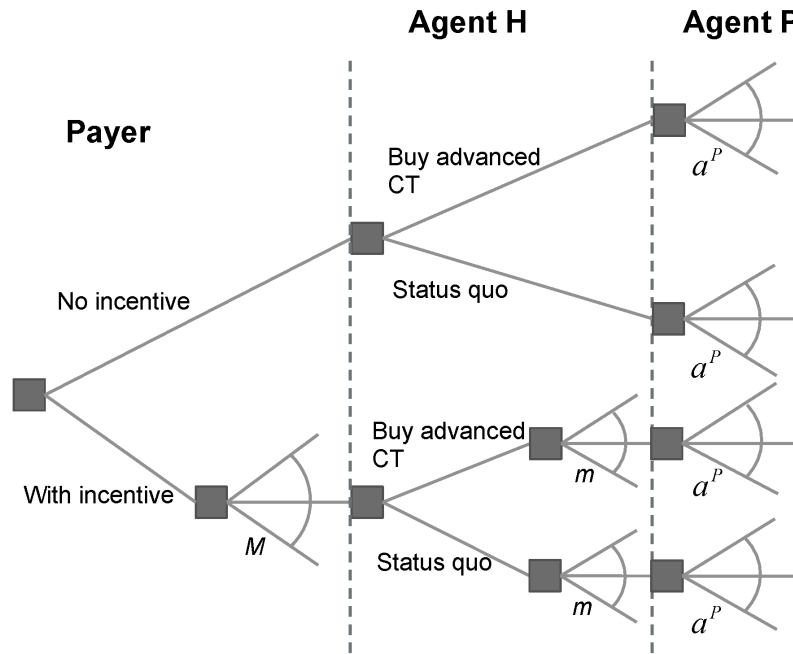


Figure 3.3: Game structure

3.2 Agents' Decision Processes

We model the agents as risk-neutral and rational, i.e., agents maximize their expected payoffs by calculating their payoffs and the payoffs of other agents, and choose decisions according to the Nash equilibrium concept. The payoffs of agents H and P are multi-attribute objective functions: agent H aims to minimize cost, while maximizing hospital reputation; agent P aims to maximize its income (FFS+incentive), while maximizing health outcomes for patients.

3.2.1 Hospital – Agent H

The decisions (actions) by agent H are notated by a_h^H , with a_1^H signifying *buy advanced CT scanner*, and a_2^H referring to *status quo*. Agent H's action a_h^H has a one-time investment cost $k(a_h^H)$, with cost parameters

$$k(a_h^H) = \begin{cases} k_1, & \text{for } a_1^H \\ k_2, & \text{for } a_2^H \end{cases}. \quad (3.1)$$

Additionally, decision a_h^H results in a maintenance cost. We distinguish between a high cost and a low cost outcome, which are represented by states s_1^H and s_2^H , respectively. Maintenance costs depend on the investment decision, but are uncertain. The uncertainty is modeled as a discrete probability $\Pr^H(s_a^H | a_h^H) = \alpha_{a;h}^H$. Each maintenance cost outcome (state) is associated with a payoff for the agent. We use the convention of MSDT and refer to payoffs as rewards. Agent H's reward associated with the maintenance cost is denoted by $r^H(s_a^H)$. Besides investment costs and maintenance costs, agent H's reward is further affected by operating costs and hospital reputation, which will be discussed in detail in Section 3.2.3.

3.2.2 Physicians – Agent P

At the physician level, the decision process is modeled structurally similar to the process at the hospital level. For each patient, a physician takes an action a_p^P , with a_1^P denoting the action *CT scan*, and a_2^P referring to an *alternative* diagnostic intervention. As discussed earlier, physicians are collectively represented by a single agent P; and $a^P \in [0, 1]$ describes the overall CT scan rate.

We model agent P's CT scan decision by building upon the concept of mental threshold values for diagnosis/treatment necessity [78]. Agent P sees a variety of patients whose conditions may or may not justify a CT scan. To decide whether a patient should receive a CT scan,

agent P estimates the necessity of ordering a CT scan based on each patient's symptoms, and then compares it with its mental threshold for administering a CT scan. Patients that fall below this threshold will not receive a CT scan, and an alternative intervention is chosen, such as an ultrasound test or a wait-and-see approach. For patients above the threshold, a CT scan is ordered.

We assume a triangular probability density function to estimate the patients' CT scan necessity, as shown in Figure 3.4. The triangular shape approximates a normal distribution and allows us to derive analytical, as opposed to only numerical, results. The necessity threshold separates a given patient population into two regions. The region under the curve to the right of the threshold represents the CT scan rate a^P of the patient population.

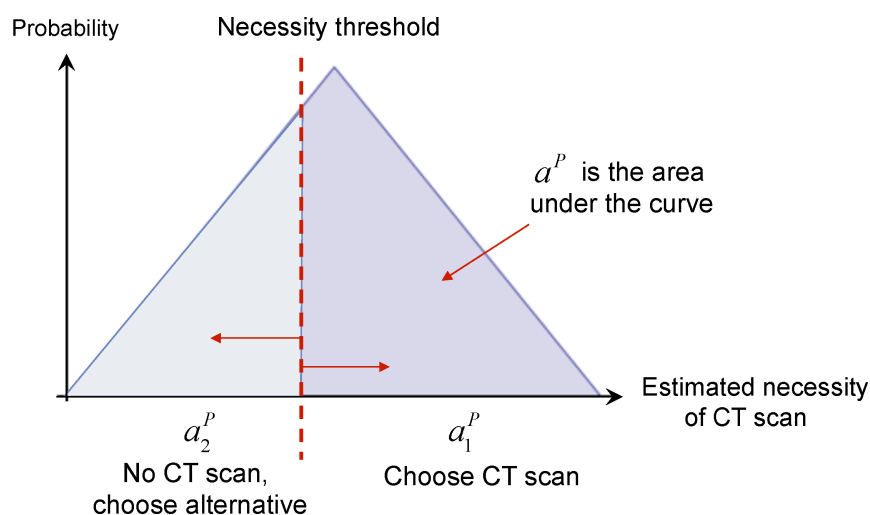


Figure 3.4: Threshold model for CT scan necessity of patient population

Each action a_p^P leads to an uncertain outcome in terms of *Medicare billings* and *health improvement*. The state space of the physicians' two-dimensional outcomes is denoted by $S^P = \{s_{1,1}^P, \dots, s_{b,c}^P, \dots, s_{B,C}^P\}$. Subscript b refers to *Medicare billings* and c to *health improvement*. Medicare billings can be either high or low, denoted by $s_{1,\cdot}^P$ and $s_{2,\cdot}^P$, respectively. The state of health improvement is also either high (due to correct diagnosis) or low (due to misdiagnosis) and depends on whether a patient had received a CT scan or not. We

differentiate between four states: $s_{,1}^P$ (CT, correct diagnosis), which includes the possibilities of both true positive and true negative testing result, $s_{,2}^P$ (CT, misdiagnosis), which includes false positive and false negative results, $s_{,3}^P$ (no CT, correct diagnosis) and state $s_{,4}^P$ (no CT, misdiagnosis). Since CT scans are a diagnostic tool, and not a treatment, we only want to capture the specificity of the diagnostic test (true vs. false) and do not differentiate between a sick or healthy patient. Figure 3.5 summarizes agent P's decision and outcomes (states).

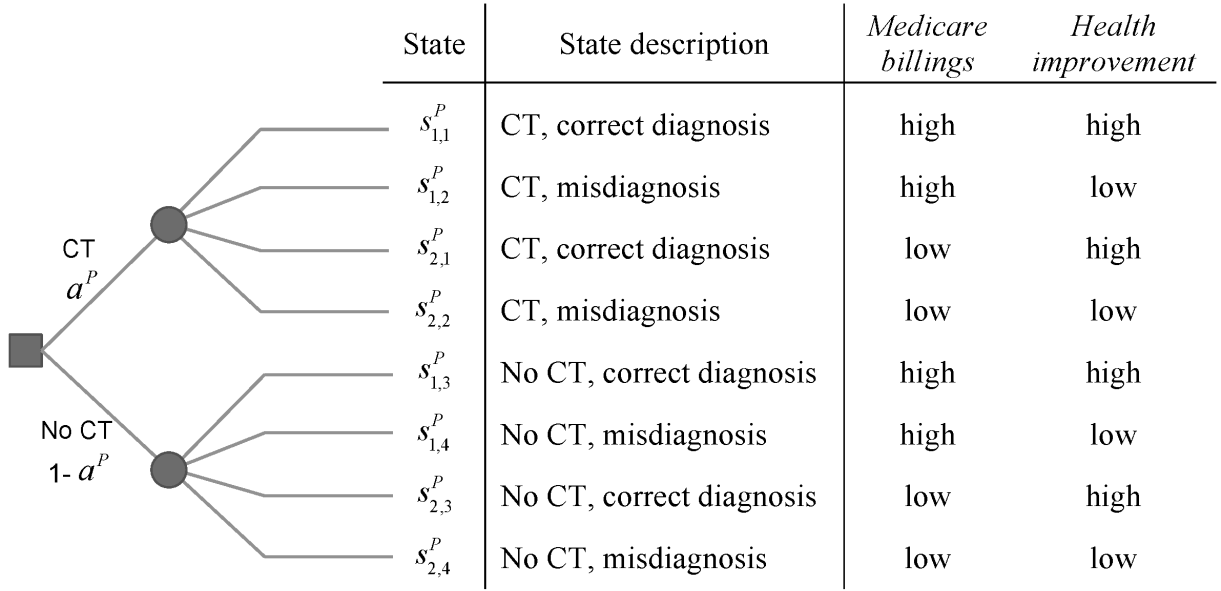


Figure 3.5: Agent P's decision tree

The probabilities of transitioning to a state given a decision are $\Pr^P(s_{b,c}^P|a_p^P) = \alpha_{b,c;p}^P$. We assume Medicare billings and health improvement are independent events, and thus $\Pr^P(s_{b,c}^P|a_p^P) = \Pr^P(s_{b,\cdot}^P|a_p^P) \cdot \Pr^P(s_{\cdot,c}^P|a_p^P) = \alpha_{b,\cdot;p}^P \cdot \alpha_{\cdot,c;p}^P$.

Each state is associated with a reward function $r^P(s_{b,c}^P)$. We assume that the rewards of the two dimensions are additive, i.e., $r_{total}^P(s_{b,c}^P) = r^P(s_{b,\cdot}^P) + r^P(s_{\cdot,c}^P)$.

3.2.3 Interdependencies Between Agent H and Agent P

The decision processes of agents H and P influence each other through two types of interdependencies, (1) and (2), as introduced in the agent interdependency diagram (Figure 3.2). Agent interdependencies are further specified in a *detailed graphical representation* as shown in Figure 3.6. The detailed graphical representation is step 2 of the MSDT modeling approach after the agent interdependency diagram had been created in step 1. Step 3 is the mathematical formulation, discussed next.

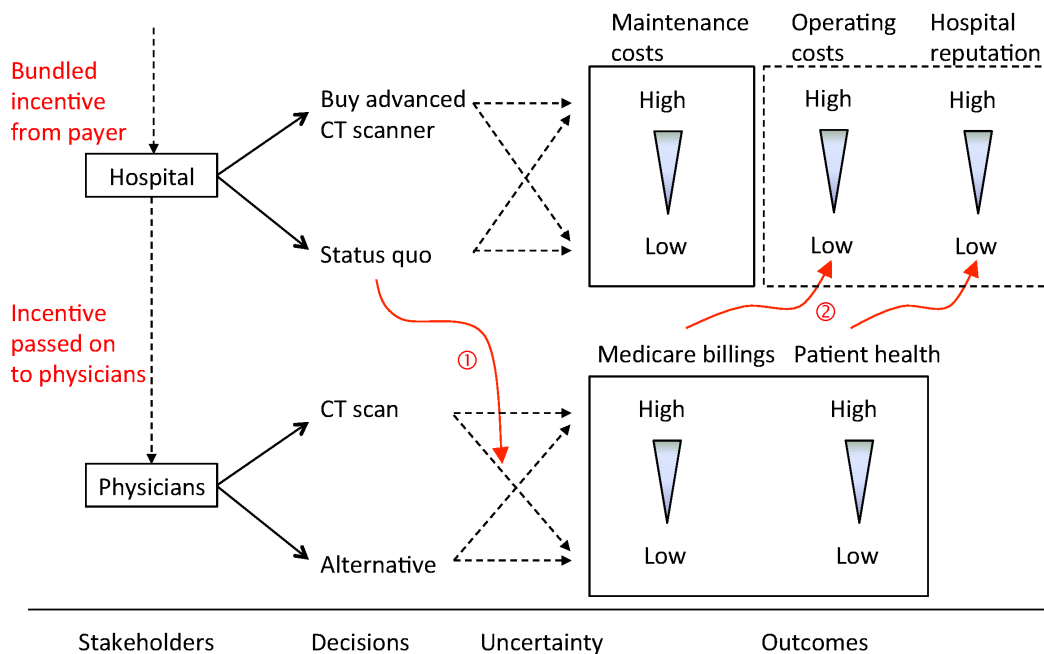


Figure 3.6: Detailed graphical representation of hospital-physician interdependencies

Interdependency (1) is the influence of agent H's decision a_h^H on the transition probability $\Pr^P(s_{b,c}^P|a_p^P)$ of agent P. Here, the hospital's decision of upgrading its CT scanner affects the CT scan accuracy. To capture this interdependency, the probabilities for a correct diagnosis given a CT scan are modified through an *additive change function* with a *change coefficient* Δ such that

$$\Pr_{final}^P (s_{:,1}^P | a_1^P, a_h^H) = \begin{cases} \Pr^P (s_{:,1}^P | a_1^P) + \Delta, & \text{if } h = 1 \\ \Pr^P (s_{:,1}^P | a_1^P), & \text{if } h = 2 \end{cases}, \quad (3.2)$$

$$\Pr_{final}^P (s_{:,2}^P | a_1^P, a_h^H) = \begin{cases} \Pr^P (s_{:,2}^P | a_1^P) - \Delta, & \text{if } h = 1 \\ \Pr^P (s_{:,2}^P | a_1^P), & \text{if } h = 2 \end{cases}. \quad (3.3)$$

Interdependency (2) describes the influence of agent P's states on agent H's reward. While maintenance costs only depend on agent H's decision, operating costs and hospital reputation are determined solely by the state of agent P. We indicate the sole source of influence by a separate dashed line box in Figure 3.6. Higher Medicare billings of physicians are linked to higher operating costs for the hospital. Similarly, greater health improvements at the physician level lead to an increase in hospital reputation. In summary, the hospital's reward function is affected by the physician-level Medicare billings and patient health outcomes, which we model via a *reward influence function*

$$r^{P \rightarrow H} (s_{b,c}^P) = \gamma_b \cdot r^P (s_{b,\cdot}^P) + \gamma_c \cdot r^P (s_{\cdot,c}^P). \quad (3.4)$$

with scaling coefficients γ_b and γ_c . Agent H's total reward, before incentives, is thus

$$r_{total}^H (a_h^H, s_a^H, s_{b,c}^P) = k (a_h^H) + r^H (s_a^H) + r^{P \rightarrow H} (s_{b,c}^P). \quad (3.5)$$

3.2.4 Incentives

The incentive offered by the payer depends on the total costs generated by agents H and P. We assume that agent H's maintenance and operating cost is the basis for the reimbursement by the payer. The hospital-level cost considered by the payer is

$$r_{cost}^H (s_a^H, s_{b,\cdot}^P) = r^H (s_a^H) + \gamma_b \cdot r^P (s_{b,\cdot}^P). \quad (3.6)$$

For the physician, Medicare Billings are reimbursed, and the physician-level cost is

$$r_{cost}^P(s_{b,\cdot}^P) = r^P(s_{b,\cdot}^P). \quad (3.7)$$

The payer's incentive program is specified by the cost benchmark M and the share μ that the ACO receives based on the generated savings. The bundled incentive payment to the ACO is

$$g^{ACO}(s_a^H, s_{b,\cdot}^P) = \mu \cdot [M - r_{cost}^H(s_a^H, s_{b,\cdot}^P) - r_{cost}^P(s_{b,\cdot}^P)]. \quad (3.8)$$

ACO internally, agent H decides how much of this incentive to pass on to agent P by setting the sharing percentage m . The incentive transfer functions are

$$g^P(s_a^H, s_{b,\cdot}^P, m) = m \cdot g^{ACO}(s_a^H, s_{b,\cdot}^P), \quad (3.9)$$

$$g^H(s_a^H, s_{b,\cdot}^P, m) = (1 - m) \cdot g^{ACO}(s_a^H, s_{b,\cdot}^P). \quad (3.10)$$

3.3 Analysis Approach

Risk-neutral agents H and P base their decisions on expected rewards. The uncertainties considered in the expected reward calculation can be aggregated in one function:

$$\begin{aligned} & \Pr(s_a^H, s_{b,c}^P | a^P, a_h^H) = \\ & \Pr^H(s_a^H | a_h^H) \cdot [a^P \cdot \Pr^P(s_{b,\cdot}^P | a_1^P) \cdot \Pr_{final}^P(s_{c,\cdot}^P | a_1^P, a_h^H) + (1 - a^P) \cdot \Pr^P(s_{b,\cdot}^P | a_2^P) \cdot \Pr^P(s_{c,\cdot}^P | a_2^P)]. \end{aligned} \quad (3.11)$$

Using this aggregated probability function and the aforementioned reward influence and incentive transfer functions, the expected values of incentives and rewards, given agents' decisions, can be calculated. The expected rewards of agents H and P are

$$E(r_{total}^H | a_h^H, a^P) = \sum_a \sum_b \sum_c r_{total}^H(a_h^H, s_a^H, s_{b,c}^P) \cdot \Pr(s_a^H, s_{b,c}^P | a^P, a_h^H), \quad (3.12)$$

$$E(r_{total}^P | a_h^H, a^P) = \sum_a \sum_b \sum_c r_{total}^P(s_{b,c}^P) \cdot \Pr(s_a^H, s_{b,c}^P | a^P, a_h^H). \quad (3.13)$$

The expected incentives for agents H and P, i.e., $E(g^H | a_h^H, m, a^P)$ and $E(g^P | a_h^H, m, a^P)$, can be determined in the same fashion.

The final rewards for agents H and P consist of the expected rewards (before incentives) and the expected incentives:

$$E(r_{final}^H | a_h^H, m, a^P) = E(r_{total}^H | a_h^H, a^P) + E(g^H | a_h^H, m, a^P), \quad (3.14)$$

$$E(r_{final}^P | a_h^H, m, a^P) = E(r_{total}^P | a_h^H, a^P) + E(g^P | a_h^H, m, a^P). \quad (3.15)$$

Each agent chooses decision(s) to maximize its expected final reward in a sequential way. We derive the subgame perfect Nash equilibrium (SPNE) for the agents' sequential game through backward induction [120, 121].

We begin with the analysis with the payer's decision branch of no incentives. Knowing agent H's investment decision a_h^H , agent P chooses the optimal CT scan rate a^{P*} to maximize its expected reward

$$a^{P*} = \arg \max_{a^P \in [0,1]} E(r_{total}^P | a_h^H, a^P). \quad (3.16)$$

Anticipating agent P's best response a^{P*} , agent H chooses the optimal investment decision a_h^{H*} that maximize its expected reward:

$$a_h^{H*} = \begin{cases} a_1^H, & \text{if } E(r_{total}^H | a_1^H, a^{P*}) > E(r_{total}^H | a_2^H, a^{P*}) \\ a_2^H, & \text{if } E(r_{total}^H | a_1^H, a^{P*}) < E(r_{total}^H | a_2^H, a^{P*}) \\ a_1^H \text{ or } a_2^H, & \text{otherwise} \end{cases} \quad (3.17)$$

For the decision branch with incentives, the analysis of agents H and P is the same, except that they now take the incentive sharing percentage m^* into account:

$$m^* = \arg \max_{m \in [0,1]} E(r_{final}^H | a_h^{H^*}, m, a^{P^*}). \quad (3.18)$$

3.4 Numerical Analysis and Results

To demonstrate the modeling results, we use a numerical example summarized in Table 3.2. For all calculations, in particular the expected reward maximization problems, we used the numerical solver of Mathematica®.

Note that in Table 3.2, the estimated CT necessity of individual patient is denoted by a random variable X , which is triangularly distributed (Figure 3.4). We assume that in the case of correct diagnosis using CT, the CT necessity of individual patient corresponds to the patient's health improvement value. A greater value of necessity implies that a CT scan is more important for physicians to make the correct clinical diagnosis and results in a greater health improvement value. Hence, the reward of health improvement is the expectation of the estimated necessity for the given patient cases.

We start the analysis with a base case where the incentive sharing percentage has a fixed value. In the following section, we allow the incentive sharing percentage and benchmark to vary and determine the optimal incentive distribution mechanism.

3.4.1 Base Case: Optimal Decisions of Payer, Hospital and Physicians

For the base case, we assume a fixed sharing percentage $m=0.5$ and the benchmark $M=35$. We follow the sequential game analysis approach to find SPNE, as described earlier. Agents' optimal decisions, and the associated rewards are shown in Figure 3.7.

The analysis shows that the payer can achieve a reduction in CT scan rate from 0.7207 to 0.6661, i.e., a 5.46 percent point change, by offering an incentive. The reduction is

Table 3.2: Parameter values for numerical analysis

Parameter	Value	Note
Payer		
Bundled incentive share of cost savings	$\mu = 50\%$	
Agent H		
Action cost	$K = \begin{cases} k_1 = -4, & \text{if } a_1^H = 1 \\ k_2 = 0, & \text{if } a_2^H = 1 \end{cases}$	
Reward of direct cost	$r^H(s_1^H) = -10, r^H(s_2^H) = -8$	
Transition probability	$\Pr^H(s_1^H a_1^H) = 0.9, \Pr^H(s_2^H a_1^H) = 0.1,$ $\Pr^H(s_1^H a_2^H) = 0.1, \Pr^H(s_2^H a_2^H) = 0.9$	
Agent P		
Reward of Medicare billings	$r^P(s_{1,\cdot}^P) = 5$ $r^P(s_{2,\cdot}^P) = 3$	High billings Low billings
Reward of health improvement	$r^P(s_{\cdot,1}^P) = E[X X \geq F^{-1}(1 - a^P)],$ $f_X(x min, max, mode) = f_X(x -60, 100, 20)$	Correct diagnosis using CT*
	$r^P(s_{\cdot,2}^P) = -20$	Misdiagnosis using CT
	$r^P(s_{\cdot,3}^P) = 20$	Correct diagnosis without CT
	$r^P(s_{\cdot,4}^P) = -20$	Misdiagnosis without CT
Transition probability	$\Pr^P(s_{1,\cdot}^P a_1^P) = 0.8, \Pr^P(s_{2,\cdot}^P a_1^P) = 0.2,$ $\Pr^P(s_{1,\cdot}^P a_2^P) = 0.2, \Pr^P(s_{2,\cdot}^P a_2^P) = 0.8$	Medicare billings
	$\Pr^P(s_{\cdot,1}^P a_1^P) = 0.8, \Pr^P(s_{\cdot,2}^P a_1^P) = 0.2,$ $\Pr^P(s_{\cdot,1}^P a_2^P) = 0.5, \Pr^P(s_{\cdot,2}^P a_2^P) = 0.5$	Health outcomes
Interdependencies		
Change function coefficient	$\Delta = 0.15$	
Reward influence function coefficient	$\gamma_b = -4$	
	$\gamma_c = 1$	

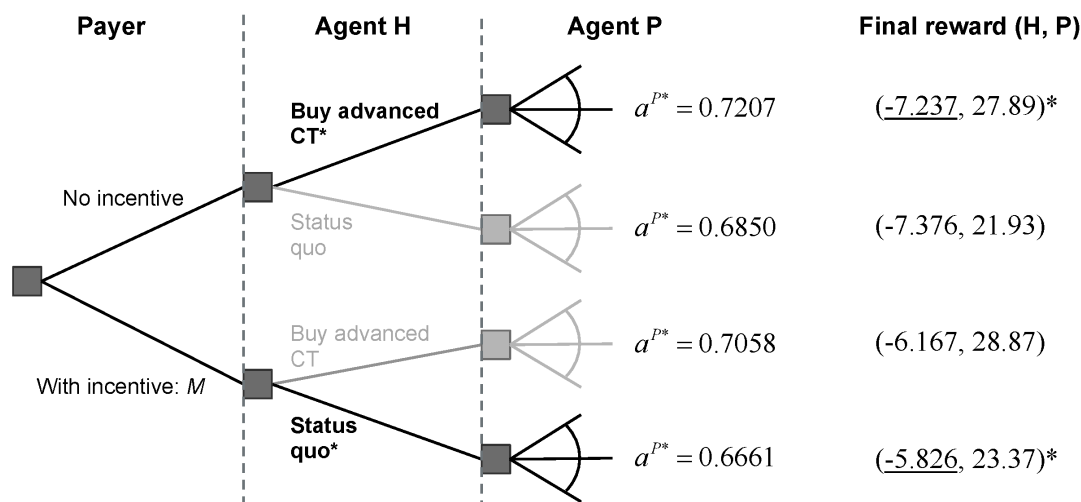


Figure 3.7: Equilibrium results of base case

a combination of two effects: (1) payer incentives discourage hospital from CT scanner purchase which in turn reduces CT scan rate, and (2) payer incentives directly motivate physicians to reduce CT scan rate.

First, we analyze the magnitude of effect (1). If no incentive is offered, agent H's optimal decision is a_1^H (buy advanced CT scanner), which, due to the CT scanner's improved diagnostic capabilities, increases agent P's optimal scan rate a^{P*} from 0.6850, under status quo, to 0.7207 – a 3.57 percent point increase. In the scenario with incentives, agent H's optimal decision is a_2^H (status quo), and the not buying a CT scanner decision leads to a CT scan reduction of 3.97 percent points (0.7058-0.6661).

Analyzing effect (2), we find that given the purchase of a new CT scanner, the incentive reduces a^{P*} from 0.7207 to 0.7058, a 1.49 percent point reduction. Given no equipment purchase, the effect of the incentive on a^{P*} is even more pronounced: a 1.89 percent point reduction (0.6850-0.6661). Comparing both effects, we see that investment effect (1) is stronger than the incentive effect (2) in this numerical example.

Figure 3.8 graphically illustrates the effect of incentive and investment on CT scan rate and physicians' reward. Comparing physicians' rewards under all four possible investment and

incentive scenarios, we see that the investment effect (1) is also stronger than the incentive effect (2) with respect to physician rewards.

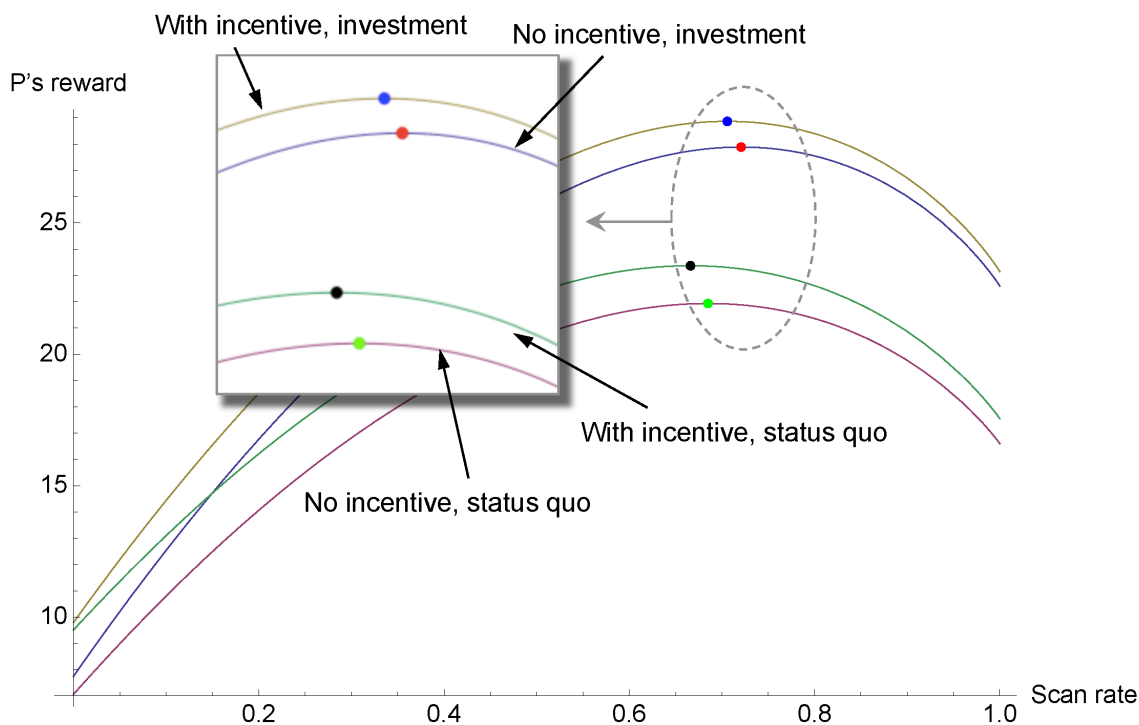


Figure 3.8: Agent P's optimal scan rate and final reward

Of course, these results depend on the parameters chosen in the numerical example. Therefore, we analyzed the effect of two key parameters: the investment cost k_1 (CT scan purchase price) and the diagnosis rate improvement Δ . We conducted a sensitivity analysis for these parameters. Figure 3.9 shows the parameters' effect on the hospital's investment decision.

The areas *status quo* and *buy CT scanner* are separated by phase transition lines, which indicate at which values of k_1 and Δ a switch of optimal decision occurs. The line to the lower left indicates the phase transition given no incentive, while the upper right line demarcates the phase transition with incentives. The area where $k_1 > 0$ is infeasible, since this would imply an income, not an expense resulting from the purchase. Not surprisingly, a high diagnosis rate improvement and a low investment cost favor the purchase of a CT

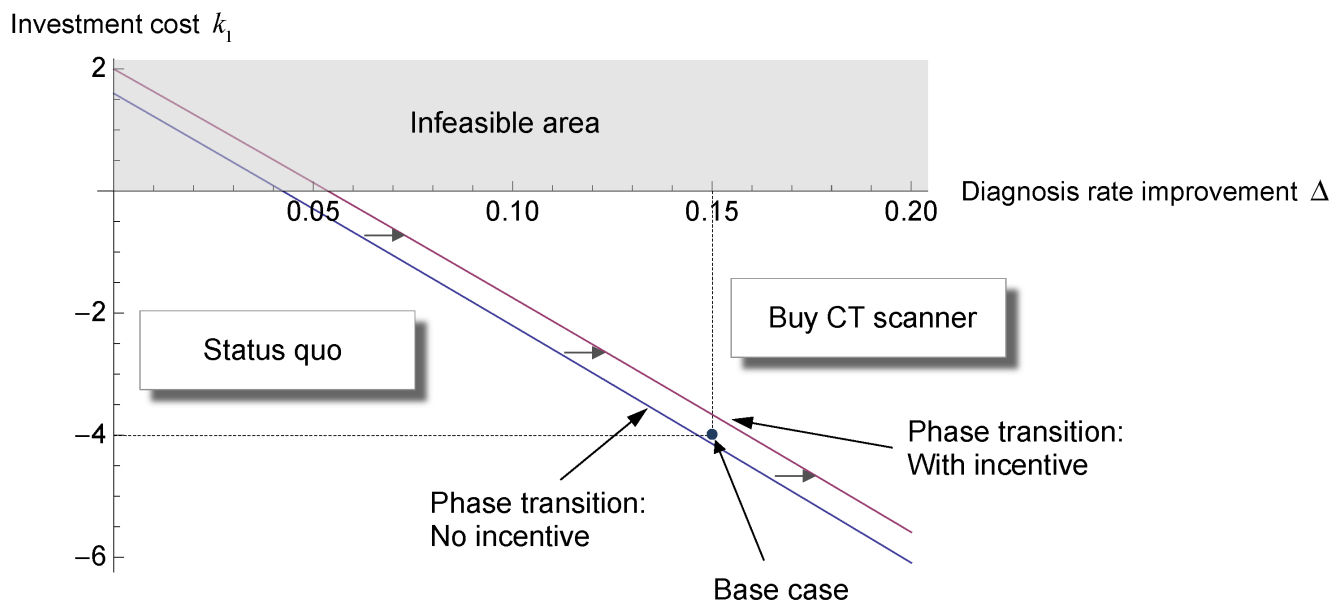


Figure 3.9: Sensitivity analysis of agent H's optimal decision

scanner.

With incentives, the transition line shifts to the right, which means that for the same investment cost, an investment has to generate higher improvement in CT scan accuracy to motivate a purchase. Similarly, for the same level of CT scan accuracy improvement, an investment has to be less expensive to trigger a purchase by agent H. In conclusion, the incentive reduces agent H's investment propensity.

The functional form of the phase transition lines can be determined analytically, but equations are too large to display effectively. We derive a linear approximation based on the numerical example of the phase transition lines, which are shown in Table 3.3.

Table 3.3: Phase transition lines of agent H's investment decision (linear approximations)

	No incentive	With incentive
Investment: $E(r_{final}^H a_1^H, a^{P*}) > E(r_{final}^H a_2^H, a^{P*})$	$0 \geq k_1 > 1.6 - 38.4\Delta$	$0 \geq k_1 > 2.0 - 37.9\Delta$
Status quo: $E(r_{final}^H a_1^H, a^{P*}) < E(r_{final}^H a_2^H, a^{P*})$	$k_1 < 1.6 - 38.4\Delta \leq 0$	$k_1 < 2.0 - 37.9\Delta \leq 0$

3.4.2 Optimal Incentive Distribution Mechanism: Effect of Cost Benchmark M

So far, we have assumed that the cost benchmark M is given. However, the payer can vary this benchmark, and we explore its effect in this section. Table 3-4 shows how the optimal decisions of agents H and P, the incentive from the payer, and the final rewards change as the benchmark M changes. The shaded area indicates the optimal decisions and outcomes of agents. The switch points of decision variables are marked with boxes.

When benchmark M is sufficiently large, agent H's optimal strategy is to keep the entire incentive to itself ($m^* = 0$). When M is sufficiently small, agent H will give the entire incentive to agent P ($m^* = 1$) as it maximizes agent H's reward. The reason is that for large M , which is a less demanding cost benchmark that results in higher incentives from the payer, agent H benefits more from keeping the incentive than from the cost savings that results from the change in agent P's decision if the incentive is passed on. In contrast, for small M , and consequentially low incentives from the payer, agent H benefits more from the cost savings resulting from agent P's reduction of CT scan rates. Hence, agent H passes on the entire incentive to induce the most significant change in agent P's decision.

Benchmark M also affects agent H's optimal investment decision a_h^{H*} . For large values of M (here, $M \geq 30$), agent H's optimal decision is status quo. For small M values, i.e., a more challenging cost benchmark, agent H's optimal response is to invest in a new CT scanner. The reason for the change in a_h^{H*} is mainly due to the switch of the optimal sharing

percentage m^* from 0 and 1 that coincided with the change in agent H's decision. For $m^* = 1$, agent H passes on all incentives to agent P, thus does not benefit from cost savings, and consequentially prefers to buy a new CT scanner resulting in higher cost (i.e., more profit for agent H) and improved hospital reputation. For $m^* = 0$, agent H keeps all incentives and thus prefers status quo as it reduces hospital costs and increases incentive payments from the payer.

The switch of agent H's investment decision a_h^{H*} and the switch of sharing percentage m^* do not necessarily occur together. For example, changes in k_1 alone can lead to a change in a_h^{H*} , without affecting m . In other words, agent H's optimal investment decision cannot be determined by a single variable or phenomenon, but needs to be evaluated based on all relevant data.

Another observation is that for a given value of m^* , i.e., $m^* = 0$ or $m^* = 1$, agent P's optimal scan rate a^{P*} is not affected by M . In fact, the analytical solution of a^{P*} does not contain variable M , which confirms the observation of the numerical analysis shown in Table 3.4 (due to the size of the analytical solutions, it is not shown here). This means a change in M does not necessarily affect agent P's decision. A change in agent P's decision can only be achieved if the change in M results in a change in agent H's decisions, i.e., investment decision or incentive distribution decision.

For $m^* = 0$, agent P's decision is not altered and is identical to the scenario without incentive, implying that the cost and CT scan reduction goal of the incentive is not achieved. Only for $m^* = 1$, when agent H gives the entire incentive to agent P, is the CT scan rate reduced. For the payer, this means that it needs to set a low benchmark M to achieve the CT scan and cost reduction goal of its shared incentive program. However, a low benchmark M makes the purchase of a CT scanner more likely, which in turn increases the CT scan rate. In our numerical example, the payer's most preferred outcome (first best) of no new CT scanner purchase and CT scan rate reduction through physician incentives ($m^* = 1$) could not be achieved. For different parameters, e.g., $r^P(s_{1,\cdot}^P) = 6$ instead of 5, this first best outcome is

Table 3.4: Impact of benchmark M on rewards and decisions

M	Investment						Status quo					
	m^*	a^{P^*}	$E(r_{final}^H a_1^H, m^*, a^{P^*})$	$E(r_{final}^P a_1^H, m^*, a^{P^*})$	$g^H(a_1^H, m^*, a^{P^*})$	a^{P^*}	$E(r_{final}^H a_2^H, m^*, a^{P^*})$	$E(r_{final}^P a_2^H, m^*, a^{P^*})$	$g^H(a_2^H, m^*, a^{P^*})$	a^{P^*}	$a_h^{H^*}$	
35	0	0.7207	-5.299	27.89	1.938	0	-4.530	21.93	2.845	0.6850	a_2^H	
34	0	0.7207	-5.799	27.89	1.438	0	-5.030	21.93	2.345	0.6850	a_2^H	
33	0	0.7207	-6.299	27.89	0.9378	0	-5.530	21.93	1.845	0.6850	a_2^H	
32	0	0.7207	-6.799	27.89	0.4378	0	-6.030	21.93	1.345	0.6850	a_2^H	
31	1	0.6904	-7.101	27.87	0.02868	0	-6.530	21.93	0.8451	0.6850	a_2^H	
30	1	0.6904	-7.101	27.37	-0.4713	0	-7.030	21.93	0.3451	0.6850	a_2^H	
29	1	0.6904	-7.101	26.87	-0.9713	1	-7.204	21.84	-0.04002	0.6467	a_1^H	
28	1	0.6904	-7.101	26.37	-1.471	1	-7.204	21.34	-0.5400	0.6467	a_1^H	

possible.

Table 3.4 suggests that m^* is always either 0 or 1. However, $0 < m^* < 1$ can occur. As shown in Figure 3.10, an interval of M where m^* lies between 0 and 1 exists, but is with $[29.85, 29.95]$ very small.

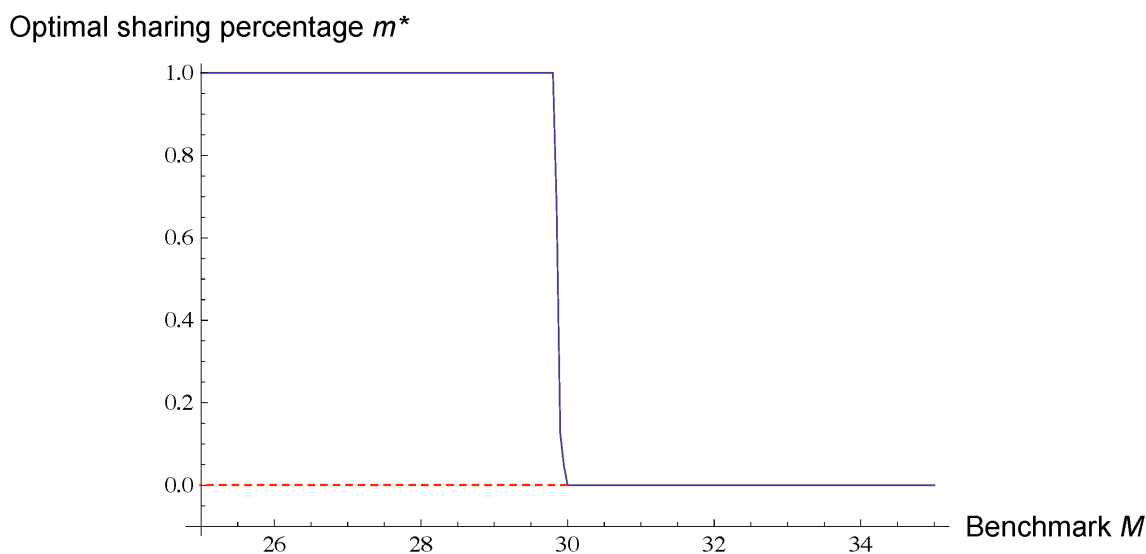


Figure 3.10: The effect of benchmark M on optimal sharing percentage m^*

To find out whether the interval is generally small, or if this is an artifact of the parameters of the numerical example, we conducted a sensitivity analysis. We varied key model parameters, one at a time, by +10% of their original value to explore the effect the interval of M where $0 < m^* < 1$. Table 3.5 summarizes the results of the analysis.

Parameter changes affect the value of M at the transition points of m^* with varying magnitudes. The maximum length of an interval is 0.8, with most of the interval lengths less than 0.17. The analysis indicates that the interval length of M for which $0 < m^* < 1$ is generally small. From a practical perspective, we can say that agent H's optimal decision of incentive sharing is either $m^* = 0$ or $m^* = 1$, and values in between are rare.

Table 3.5: Parameter sensitivity analysis

	Initial value	New value	M at transition $m^* = 1 \rightarrow m^* < 1$	M at transition $m^* > 0 \rightarrow m^* = 0$	Interval length of M for $0 < m^* < 1$
Base case	-	-	29.85	29.95	0.10
$\Pr^H (s_1^H a_1^H)$	0.9	0.99	29.3	30.0	0.7
$\Pr^H (s_1^H a_2^H)$	0.1	0.11	29.91	30.00	0.09
k_1	-4	4.4	29.82	29.99	0.17
$r^H (s_1^H)$	-10	-11	29.4	30.1	0.7
$\Pr^P (s_{1,\cdot}^P a_1^P)$	0.8	0.88	30.3	30.8	0.5
$\Pr^P (s_{1,\cdot}^P a_2^P)$	0.2	0.22	29.9	30.0	0.1
$\Pr^P (s_{\cdot,1}^P a_1^P)$	0.8	0.88	30.14	30.15	0.01
$\Pr^P (s_{\cdot,1}^P a_2^P)$	0.5	0.55	29.1	29.9	0.8
$r^P (s_{1,\cdot}^P)$	5	5.5	31.3	31.9	0.6
$f(x min, max, mode)$	(-60,20,100)	(-58,22,102)	30.87	30.88	0.01
Δ	0.15	0.165	31.02	31.03	0.01

3.5 Conclusions

This chapter considered a multi-level health care system consisting of physicians, hospital, and the payer. An analytical approach was proposed that can evaluate the multi-level effects of incentives on the use and investment of medical technologies. MSSP ACOs were chosen as the problem setting, and CT as an exemplary medical technology. Using MSDT, we modeled the decisions of agents and their responses to incentives, taking into account the effects that decisions and outcomes of agents at various levels have on one another.

We graphically captured the interactions among agents across system levels through an agent interdependence diagram and a detailed graphical representation. Based upon these graphical modeling tools, we mathematically formulated the hospital's decision process of CT investment and the physicians' decision process of CT usage. We considered the multi-attribute objective functions of hospitals and physicians. Hospitals consider profits and hospital reputation, while physicians consider their income and the health of their patients.

Physicians make the CT usage decision by comparing each patient's estimated CT necessity to the mental threshold. The aggregate behavior of physicians is expressed as the CT scan rate for the patient population. Lastly, we accounted for the bidirectional influence of hospital and physician on each other's decisions and outcomes.

We analyzed the model as a sequential game. First, the payer decides how to reimburse and incentivize ACOs via MSSP by setting a cost benchmark. The ACO hospital then decides how the incentive is distributed between itself and the physicians. It also decides whether to make the CT scanner investment. At last, physicians decide the CT scan rate. We solved the game using the subgame perfect Nash equilibrium concept and backward induction. A numerical example was used, and optimal and equilibrium solutions were derived.

The numerical analysis showed that incentives could alter the CT usage decision by physicians. However, a high benchmark, and with it a high incentive, can turn out to be ineffective

in reducing the CT scan rate. The reason is that hospital will keep all incentives and not pass them on to physicians. In contrast, if the benchmark is too low, the cost target is unattainable and would result in penalty payment instead of rewards for ACOs, which could discourage ACOs to continue participating in the MSSP. At the right benchmark level, the hospital will pass on all incentives to the physicians, which in turn lowers the CT scan rate. The CT scan rate is also affected by the hospital's investment decision. A new and more advanced CT scanner will lead to more CT scans. Furthermore, a low benchmark will result in a CT scanner purchase, whereas a high benchmark will discourage an investment by the hospital.

The best outcome (first best) for the payer would be if the hospital passed on all incentives to physicians and would not buy a CT scanner. The second best outcome is achieved when the hospital passes on all incentives to physicians and makes an investment, or when the hospital keeps all the incentives and does not invest. The least desirable result is when the hospital keeps all incentives to itself and invest.

Which of these outcomes occurs depends on the system parameters, such as investment cost and effectiveness of CT scanner. To this end, the payer needs to comprehensively analyze the multi-level response of the ACO to the MSSP in order to achieve the desired results. Setting the benchmark just right is crucial to achieve lower CT scan rates, discourage unnecessary CT scanner purchase, and save costs.

As with all mathematical models of complex socio-technical systems, limitations need to be considered. We assumed that physicians are the only type of individual providers who order CT scans and get reimbursed. In reality, the utilization of CT scans is jointly decided by providers including physicians and radiologists. Furthermore, physicians who order diagnostic tests often do not receive direct payments for CT scans, and radiologists who read them do not order tests. Besides, we unified the DRG payment for hospital at a fixed payment level, whereas in reality the payment is likely to be affected by the diagnosis results, e.g., correct diagnosis or misdiagnosis. In addition to that, for the multi-attribute objective func-

tions, different agent may assign different priorities to the attributes. How to quantify the priorities of the attributes is another issue that needs to be considered. These aforementioned limitations will be partially addressed in the model extension.

Chapter 4

Multi-level Analysis of Incentives on Radiology and Accountable Care Organizations

In this chapter, we provide the multi-level decision-making model consisting of three hierarchies (payer, hospital, and individual providers) and four agents (payer, hospital, primary care physicians, and radiologists). It begins with research themes and model preliminaries. Thereafter, we elaborate on the detailed mathematical formulation and model the CT scan utilization problem and the CT scanner investment problem respectively. Later, we present the analytical solutions and numerical analysis. We compare the scenario with and without incentives, discuss the optimal incentive distribution mechanism, and give policy implications for payers.

4.1 Introduction

The previous chapter provides important insights on the multi-level decision-making modeling in health care and serves as basis for further model extension and analysis [122]. In this work, we use MSDT to extend the previous research and formulate an analytical model that captures the interactions and interdependencies among multiple health care agents, including payers, hospitals, primary care physicians and radiologists. Our model and analysis focus on MSSP incentives and its effect on decisions by health care agents, in particular the decisions of CT scan investment and usage, as well as financial and health outcomes. Further, the model evaluates and optimizes incentive mechanisms involving multiple ACO members, including hospitals, primary care physicians, and radiologists. Finally, we analyze how health care payers should design MSSP incentive policies to maximize social welfare of the patient population.

The focus of the prior chapter is on the modeling concept and mathematics of MSDT. While it made important methodological contribution to MSDT, it did not sufficiently account for health care realities and intricacies, and thus could not provide reliable practical insights. In particular, it did not consider the difference between CT-scan-prescribing physicians and radiologists, and merely assumed a single agent. Decision-making and incentives, however, are different for these two agents. Primary care physicians order CT scans, but they do not get paid for performing them. Radiologists, in contrast, cannot control the CT scan rate for diagnostic imaging, but financially benefit from higher number of referrals. The paper at hand adds the radiologist as a stakeholder, and extends the previous MSDT model by explicitly accounting for this agent. 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. Lastly, a number of modeling assumptions in Chapter 3 were removed to more realistically capture how diagnostic imaging decisions are made by primary care physicians, how screening decisions are made

by radiologists, and how these decisions and outcomes affect cost and quality across various levels of the health care system.

4.2 The Model

4.2.1 Problem Description

In our model, we consider six key stakeholders: payer, ACO, hospital, primary care physicians, radiologists and patients. We assume that patients perfectly follow physicians' diagnostic and treatment recommendations. Moreover, we assume that the hospital is the leader of the ACO and makes the incentive distribution decisions, i.e., the ACO is represented by the hospital. Lastly, we only account for the aggregate behaviors of primary care physicians and radiologists, and model each 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 4.1.

Agents make their decisions sequentially. CMS, as the policy maker, payer, and first mover, decides how to reimburse and incentivize ACOs via MSSP. Specifically, CMS determines the MSSP incentives for the ACOs by setting the cost benchmark. In the second stage, the hospital makes two types of decisions: (1) whether to invest and upgrade its current CT scanner technology, and (2) how to distribute the incentive it received from CMS, i.e., the share of incentive it gives to agents P and R, and the amount it keeps for itself. In the third and final stage, agents P and R decide upon and perform CT scans.

We consider two types of CT scan tests: (1) diagnostic tests ordered by primary care physicians and read by radiologists, and (2) screening tests for disease prevention ordered and read by radiologists. The first type serves *population 1*, consisting of patients that show certain symptoms and seek medical diagnosis and treatment. The second type serves *popu-*

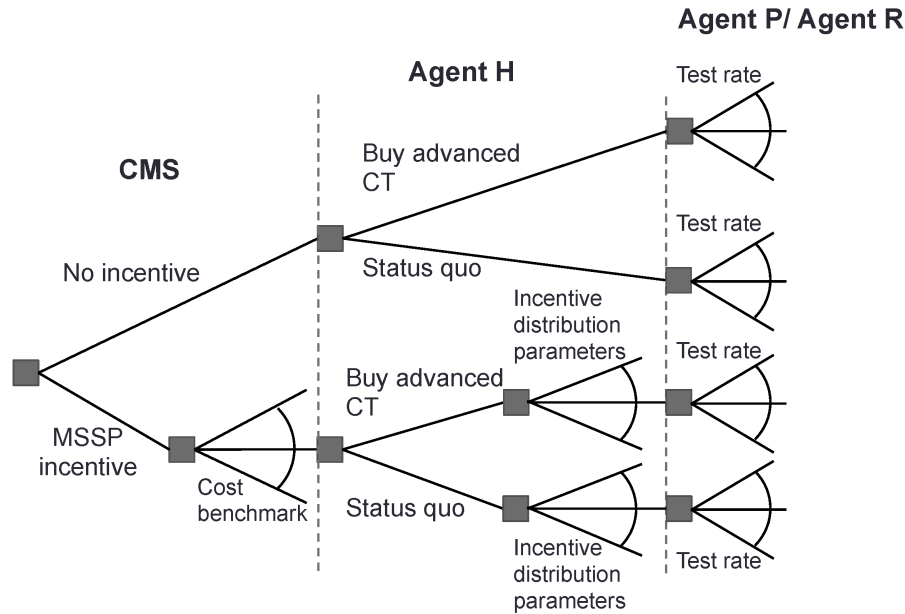


Figure 4.1: Game structure

lation 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 of population 1 is men who have pain during urination and for whom an abdominal CT scan could detect kidney stones. An example of population 2 is asymptomatic women that are at the risk of developing breast cancer and may benefit from regular screening mammograms [123]. The two populations are assumed to be *disjoint sets*; i.e., a patient is either in population 1 or 2, but cannot be in both. The number of patients in population 1 and 2 are denoted by N_1 , N_2 , respectively.

We model the agent interaction as a non-repeated game, which captures the one-time clinical interaction between a patient and a provider as well as the immediate health and cost outcomes. We do not consider temporal effects such as patients' long-term health evolution for treatments over time. However, MSDT provides the mathematical foundation for this extension in future research.

4.2.2 CT Scan Decision Problem

Agents P and R determine whether a CT scan is necessary based on patient conditions, such as symptoms, age, race, sex and family history of disease. 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 $i = 1, 2$, 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 the rank of patients is uniformly distributed across the patient populations with $x_i \sim \mathcal{U}(0, 1)$. The rank concept was adopted from Yaesoubi and Roberts (2010) [124].

Low-ranked patients, i.e., those with more severe symptoms or higher disease predispositions, have a greater *probability* $p_i(x_i)$ 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 being sick is $p_2(x_2) = r \cdot (1 - x_2)$.

Agents P and R assess a patient's rank through clinical exams and review of medical history. Depending on the rank (and thus disease probability), a diagnostic or screening CT test for a patient is medically more or less justified and beneficial [125]. We assume that agents P and R have established a *testing threshold* θ_P and θ_R , respectively. The concept of a testing threshold was proposed by Pauker and Kassirer (1980) [78]. In their work, the threshold corresponds to the probability of disease at which the physician is indifferent between performing and not performing a test. Having observed rank x_i , 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 that are healthy, i.e., $x_1 > \theta_P$ and $x_2 > \theta_R$, no CT scan is ordered.

At an aggregate patient level, the testing thresholds θ_P and θ_R correspond to the CT test rate of agents P and R, respectively. Given the uniform distribution $\mathcal{U}(0, 1)$, the CT test rates for agents P and R are θ_P and θ_R , respectively.

4.2.2.1 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 test rate θ_P to maximize a two-attribute utility function consisting of *health benefit* and *monetary payoff*.

We define the state space of each individual patient as a 3-tuple [126], with

$$\{\textit{true health status}, \textit{imaging decision}, \textit{treatment decision}\}.$$

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 patient is given a CT scan. A correct diagnosis leads to *true positive* or *true negative* cases; whereas a misdiagnosis leads to *false positive* or *false negative* cases. Treatments will be performed only when positive results are found through imaging. 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., $q \in (0.5, 1)$. Table 4.1 summarizes the probabilities for a patient with rank x_1 transitioning to one of the six possible states. The probabilities in each column add up to 1.

Health benefit:

We denote the health benefit for each patient state by value μ . The health benefit depends on

Table 4.1: Transition probabilities associated with patient states (diagnostic)

State	Patient rank		
	$x_1 \leq \theta_P$		$x_1 > \theta_P$
	Imaging result	Transition probability	Transition probability
$\{S, I, T\}$	True positive	$p_1(x_1) \cdot q$	0
$\{S, I, N\}$	False negative	$p_1(x_1) \cdot (1 - q)$	0
$\{H, I, N\}$	True negative	$[1 - p_1(x_1)] \cdot q$	0
$\{H, I, T\}$	False positive	$[1 - p_1(x_1)] \cdot (1 - q)$	0
$\{H, A, N\}$	N/A	0	$1 - p_1(x_1)$
$\{S, A, N\}$	N/A	0	$p_1(x_1)$

a patient's state, i.e., Sick vs. Healthy, Imaging vs. Alternative/no imaging and Treatment vs. No treatment. We can 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 sick or health person correctly, i.e., no imaging/treatment when healthy and imaging/treatment, are the same ($\mu_{H,A,N} = \mu_{S,I,T}$). Taken together, the health status values can be order as

$$\mu_{H,A,N} = \mu_{S,I,T} > \mu_{H,I,N} > \mu_{H,I,T} > \mu_{S,A,N} > \mu_{S,I,N}.$$

Monetary payoff:

Agents P and R are reimbursed based on an FFS basis (not accounting for incentives). Agent R receives a fixed payment $c_I > 0$ 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, agent P receives monetary payoffs, which can be ordered

as follows: $c_{H,I,T} = c_{S,I,T} > c_{H,I,N} = c_{S,I,N} > c_{H,A,N} = c_{S,A,N}$. The rationale for this order is that 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, and thus $c_{H,I,T} = c_{S,I,T} > c_{H,I,N} = c_{S,I,N} > c_{H,A,N} = c_{S,A,N} = 0$.

The decision process of diagnostic imaging, and the associated probability and payoffs can be summarized in a decision tree (Figure 4.2).

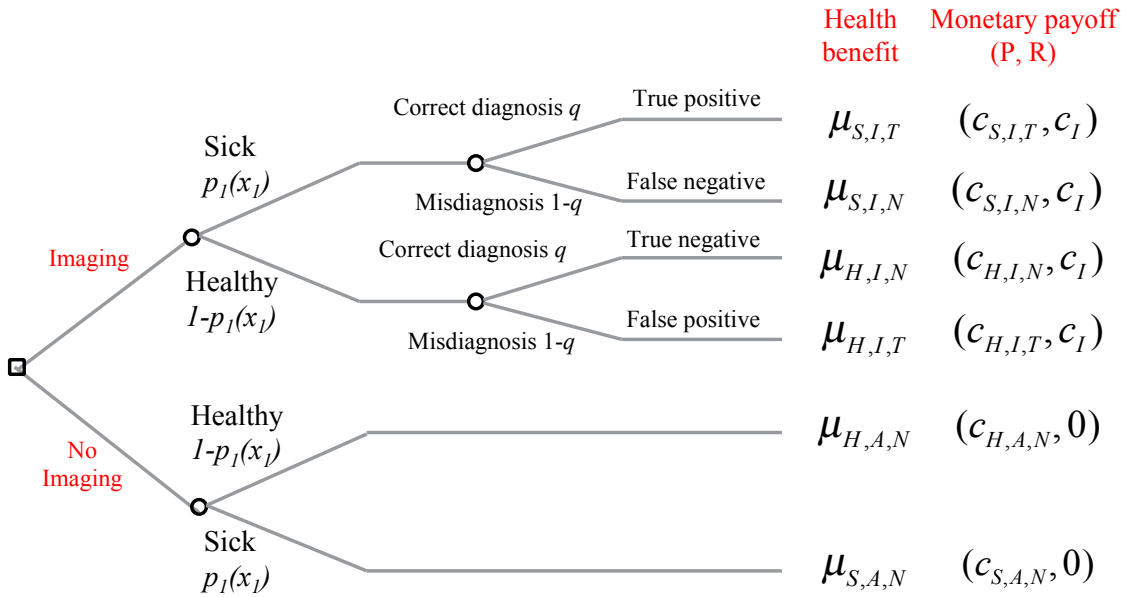


Figure 4.2: The diagnostic CT scan decision process

4.2.2.2 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 test rate θ_R for population 2, maximizing the two-attribute utility function consisting of health benefit and monetary payoff. Following the process in Section 4.2.2.1, 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 4.1.

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 4.2.

4.2.3 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 $k(a_2) = k_2$. 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 δ , with $\delta \in (0, 1 - q]$, such that the resulting probability is

$$q(a_h) = \begin{cases} q + \delta, & \text{if } h = 1 \\ q, & \text{if } h = 2 \end{cases} . \quad (4.1)$$

4.2.4 Utility Functions of Agents

Interdependencies exist among the decisions and outcomes of agents H, P and R. We use the *detailed graphical representation* of the MSDT modeling approach to illustrate agent interdependencies, thereby connecting the three system levels. In Figure 4.3, the red arrows (labeled by (1) and (2)) 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. 4.1. Interdependency (2) is the influence of agents P and R’s outcomes on agent H’s outcome (see later Section 4.2.4.3 for the mathematical formulation of interdependencies).

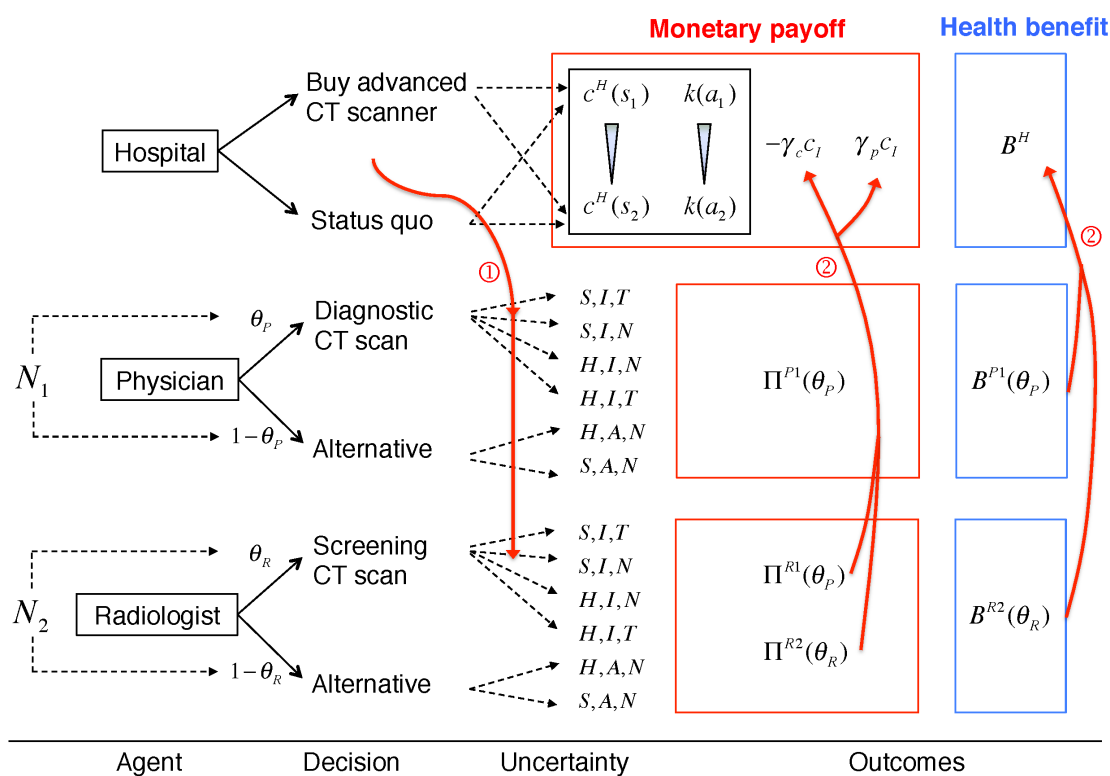


Figure 4.3: Detailed graphical representation of agent interdependencies

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. In the following sections, we discuss the utility function of each agent

(not yet accounting for incentives, which are analyzed in Section 4.3).

4.2.4.1 Agent P

Agent P cares about its monetary payoff, denoted by Π^{P1} , and the well-being of its patients, expressed by 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 $\lambda^P > 0$ as a scaling factor for B^{P1} . We assume risk neutrality and linear monetary preferences. Agent P's decision problem is to choose diagnostic test rate θ_P , given agent H's investment decision a_h , that maximizes its utility U^P , i.e.,

$$\max_{0 \leq \theta_P \leq 1} U^P(\theta_P|a_h) = \Pi^{P1}(\theta_P|a_h) + \lambda^P \cdot B^{P1}(\theta_P|a_h). \quad (4.2)$$

The agent monetary payoff, given population 1's patient number N_1 , is calculate by

$$\begin{aligned} \Pi^{P1}(\theta_P|a_h) = N_1 \cdot [& c_{S,I,T} \int_0^{\theta_P} p_1(x_1) \cdot \tilde{q} dx_1 + c_{S,I,N} \int_0^{\theta_P} p_1(x_1) \cdot (1 - \tilde{q}) dx_1 + c_{H,I,N} \int_0^{\theta_P} (1 - p_1(x_1)) \cdot \tilde{q} dx_1 \\ & + c_{H,I,T} \int_0^{\theta_P} (1 - p_1(x_1)) \cdot (1 - \tilde{q}) dx_1 + c_{H,A,N} \int_{\theta_P}^1 (1 - p_1(x_1)) dx_1 + c_{S,A,N} \int_{\theta_P}^1 p_1(x_1) dx_1]. \end{aligned} \quad (4.3)$$

and the health benefit value is determined by

$$\begin{aligned} B^{P1}(\theta_P|a_h) = N_1 \cdot [& \mu_{S,I,T} \int_0^{\theta_P} p_1(x_1) \cdot \tilde{q} dx_1 + \mu_{S,I,N} \int_0^{\theta_P} p_1(x_1) \cdot (1 - \tilde{q}) dx_1 + \mu_{H,I,N} \int_0^{\theta_P} (1 - p_1(x_1)) \cdot \tilde{q} dx_1 \\ & + \mu_{H,I,T} \int_0^{\theta_P} (1 - p_1(x_1)) \cdot (1 - \tilde{q}) dx_1 + \mu_{H,A,N} \int_{\theta_P}^1 (1 - p_1(x_1)) dx_1 + \mu_{S,A,N} \int_{\theta_P}^1 p_1(x_1) dx_1]. \end{aligned} \quad (4.4)$$

4.2.4.2 Agent R

Agent R's utility depends on both the diagnostic test rate θ_P for population 1 and the screening test rate θ_R for population 2. From population 1, agent R obtains only FFS payment for test interpretation, denoted by $\Pi^{R1}(\theta_P)$. From population 2, agent R obtains monetary payoff $\Pi^{R2}(\theta_R)$ and health benefit $B^{R2}(\theta_R)$. Multiplier $\lambda^R > 0$ expresses this agent's tradeoff preferences between monetary payoff and patients' health. Agent R's decision problem and utility function are

$$\max_{0 \leq \theta_R \leq 1} U^R(\theta_R, \theta_P | a_h) = \Pi^{R1}(\theta_P) + \Pi^{R2}(\theta_R) + \lambda^R \cdot B^{R2}(\theta_R | a_h). \quad (4.5)$$

Agent R's monetary payoff value is simply calculate by

$$\Pi^{R1}(\theta_P) + \Pi^{R2}(\theta_R) = N_1 \cdot \theta_P \cdot c_I + N_2 \cdot \theta_R \cdot c_I. \quad (4.6)$$

and the health benefit value is determined by

$$\begin{aligned} B^{R2}(\theta_R | a_h) = & N_2 \cdot [\mu_{S,I,T} \int_0^{\theta_R} p_2(x_2) \cdot \tilde{q} dx_2 + \mu_{S,I,N} \int_0^{\theta_R} p_2(x_2) \cdot (1 - \tilde{q}) dx_2 + \mu_{H,I,N} \int_0^{\theta_R} (1 - p_2(x_2)) \cdot \tilde{q} dx_2 \\ & + \mu_{H,I,T} \int_0^{\theta_R} (1 - p_2(x_2)) \cdot (1 - \tilde{q}) dx_2 + \mu_{H,A,N} \int_{\theta_R}^1 (1 - p_2(x_2)) dx_2 + \mu_{S,A,N} \int_{\theta_R}^1 p_2(x_2) dx_2]. \end{aligned} \quad (4.7)$$

4.2.4.3 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 all patients' health benefits (with scaling factor $\lambda^H > 0$):

$$\max_{a_h} U^H(a_h) = \Pi^H(a_h) + \lambda^H \cdot [B^{P1}(\theta_P) + B^{R2}(\theta_R)]. \quad (4.8)$$

Agent H's monetary payoff Π^H is revenue minus costs. Each imaging test ordered by agents P or R incurs a fixed payment (revenue) to agent H according to the OPSS system and a fixed operating cost. To map the interdependencies between agents P and R's monetary

payoff and agent H's outcome (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

$$\begin{aligned}\Pi^H(a_h) &= \sum_a -c^H(s_a) \cdot \Pr(s_a|a_h) - k(a_h) + (\gamma_p - \gamma_c)(c_I N_1 \theta_P + c_I N_2 \theta_R) \\ &= \sum_a -c^H(s_a) \cdot \Pr(s_a|a_h) - k(a_h) + (\gamma_p - \gamma_c) \cdot [\Pi^{R1}(\theta_P) + \Pi^{R2}(\theta_R)].\end{aligned}\quad (4.9)$$

4.2.4.4 CMS

CMS's utility function can be interpreted as maximizing 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

$$\max_M U^{CMS}(M) = -\Pi^{ACO} - I + \lambda^{CMS} \cdot [B^{P1}(\theta_P) + B^{R2}(\theta_R)].\quad (4.10)$$

The relative weight λ^{CMS} in Eq. 4.10 can be defined as the *willingness-to-pay (WTP) for health*, which is the amount of money the payer is willing to spend for one unit of aggregated health benefit [124].

Specifically, the total billings of the ACO are

$$\Pi^{ACO} = \gamma_p \cdot [\Pi^{R1}(\theta_P) + \Pi^{R2}(\theta_R)] + \Pi^{P1}(\theta_P) + \Pi^{R1}(\theta_P) + \Pi^{R2}(\theta_R).\quad (4.11)$$

For the incentive part, CMS ties it directly to the cost savings achieved by the ACO when the quality goals are attained. 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

$$I(\cdot) = \eta \cdot \{M - \gamma_p \cdot [\Pi^{R1}(\theta_P) + \Pi^{R2}(\theta_R)] - \Pi^{P1}(\theta_P) - \Pi^{R1}(\theta_P) - \Pi^{R2}(\theta_R)\}. \quad (4.12)$$

4.3 Analysis

In this section, we analyze and compare two scenarios – (1) without incentive, and (2) with incentive – to examine the multi-level interdependencies and how MSSP affects agents' decisions and outcomes. To find the agents' optimal decisions in their sequential game (recall Figure 4.1), we use the subgame perfect Nash equilibrium (SPNE) concept [121]. SPNEs are solved through backward induction, i.e., the analysis begins with the final decision stage. We denote the optimal decisions without incentives by superscript * and with incentives by superscript **.

4.3.1 No Incentive

Without MSSP incentive, the following sequence of events occurs: (1) agent H chooses the optimal investment decision a_h^* ; (2) given a_h^* , agent P and agent R decides the optimal CT test rate θ_P^* and θ_R^* simultaneously (i.e., unaware of the other agent's choice).

4.3.1.1 Stage 2: Agents P and R's Decision

Given an investment decision a_h , agent P chooses a diagnostic test rate θ_P^* to maximize its utility, i.e.,

$$\theta_P^* = \arg \max_{\theta_P \in [0,1]} U^P(\theta_P | a_h) = \arg \max_{\theta_P \in [0,1]} [\Pi^{P1}(\theta_P | a_h) + \lambda^P \cdot B^{P1}(\theta_P | a_h)]. \quad (4.13)$$

Similarly, agent R's optimal screening test rate θ_R^* is

$$\theta_R^* = \arg \max_{\theta_R \in [0,1]} U^R(\theta_R, \theta_P | a_h) = \arg \max_{\theta_R \in [0,1]} [\Pi^{R1}(\theta_P) + \Pi^{R2}(\theta_R) + \lambda^R \cdot B^{R2}(\theta_R | a_h)]. \quad (4.14)$$

The detailed representation of the utility maximization problems (UMPs) of agents P and R (Eq. 4.13, 4.14) can be found in Appendix A.1. The ensuing analysis relies on the following assumption.

Assumption 1. (*Typical patient mix*) *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.*

From Assumption 1, it follows that if agents P and R only cared about patient health, but not monetary payoffs, their optimal CT scan would not be 0 or 1. The following Lemmas and Theorem provide closed-form solutions for the optimal test rates given agents' preference.

Lemma 1. *For agents P and R that care only about patient health but not monetary payoff ($\lambda^P = \infty$, $\lambda^R = \infty$), the optimal test rates are*

$$0 < \theta_P^{*h} = \frac{\mu_{S,A,N} - \tilde{q}\mu_{S,I,T} - (1 - \tilde{q})\mu_{S,I,N}}{(\mu_{S,A,N} - \mu_{H,A,N}) + (1 - \tilde{q})(\mu_{H,I,T} - \mu_{S,I,N}) + \tilde{q}(\mu_{H,I,N} - \mu_{S,I,T})} < 1, \quad (4.15)$$

$$0 < \theta_R^{*h} = 1 + \frac{\mu_{H,A,N} - \tilde{q}\mu_{H,I,N} - (1 - \tilde{q})\mu_{H,I,T}}{r \cdot [(\mu_{S,A,N} - \mu_{H,A,N}) + (1 - \tilde{q})(\mu_{H,I,T} - \mu_{S,I,N}) + \tilde{q}(\mu_{H,I,N} - \mu_{S,I,T})]} < 1, \quad (4.16)$$

with θ_P^{*h} and θ_R^{*h} denoting the health-maximizing CT test rates for agents P and R, respectively.

Proof. See Appendix. □

Lemma 2. *For agents P and R that care only about their monetary payoffs but not patient health ($\lambda^P = 0$, $\lambda^R = 0$), the optimal monetary-maximizing rates θ_P^{*m} and θ_R^{*m} are 1.*

Proof. See Appendix. □

Theorem 1. *For agents P and R that care about both monetary payoffs and patient health ($0 < \lambda^P < \infty$, $0 < \lambda^R < \infty$), the optimal test rates are*

$$\theta_P^* = \frac{c_{S,A,N} - \tilde{q}c_{S,I,T} - (1 - \tilde{q})c_{S,I,N} + \lambda^P[\mu_{S,A,N} - \tilde{q}\mu_{S,I,T} - (1 - \tilde{q})\mu_{S,I,N}]}{(1 - 2\tilde{q})(c_{H,I,T} - c_{H,I,N}) + \lambda^P[(\mu_{S,A,N} - \mu_{H,A,N}) + (1 - \tilde{q})(\mu_{H,I,T} - \mu_{S,I,N}) + \tilde{q}(\mu_{H,I,N} - \mu_{S,I,T})]}, \quad (4.17)$$

$$\theta_R^* = 1 + \frac{-c_I + \lambda^R\{\mu_{H,A,N} - \tilde{q}\mu_{H,I,N} - (1 - \tilde{q})\mu_{H,I,T}\}}{\lambda^R \cdot r \cdot [\mu_{S,A,N} - \mu_{H,A,N} + (1 - \tilde{q})(\mu_{H,I,T} - \mu_{S,I,N}) + \tilde{q}(\mu_{H,I,N} - \mu_{S,I,T})]}. \quad (4.18)$$

The optimal test rates lie between the monetary-payoff-maximizing rate and the health-benefit-maximizing rate, i.e., $\theta_P^{*h} < \theta_P^* \leq \theta_P^{*m} = 1$ and $\theta_R^{*h} < \theta_R^* \leq \theta_R^{*m} = 1$.

Proof. See Appendix. □

From Eqs. 4.17 and 4.18 we can see that θ_P^* and θ_R^* are independent from each other. While agent P's optimal test rate affects agent R's monetary payoff, it does not influence agent R's optimal test rate. Theorem 1 further shows that if agents P and R are financially rewarded for doing more tests and treatments – as they are 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.

4.3.1.2 Stage 1: Agent H's decision

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

$$a_h^* = \arg \max_{a_h} U^H(a_h) = \Pi^H(a_h) + \lambda^H \cdot B^H \quad (4.19)$$

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

$$\begin{aligned} U^H(a_h) = & \sum_a -c^H(s_a) \cdot \Pr(s_a|a_h) - k(a_h) + (\gamma_p - \gamma_c) \cdot [\Pi^{R1}(\theta_P^*) + \Pi^{R2}(\theta_R^*)] \\ & + \lambda^H \cdot [B^{P1}(\theta_P^*|a_h) + B^{R2}(\theta_R^*|a_h)]. \end{aligned} \quad (4.20)$$

We obtained the closed-form solution for Eq. 4.19 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, which is discussed in Section 4.4. 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 test rates 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-benefit-maximizing test rates θ_P^{*h} and θ_R^{*h} of agent P and R will both increase.*

(b) *For an agent P that cares about both monetary payoffs and patient health, the CT test rate increasing condition $\theta_P^*(a_2) < \theta_P^*(a_1)$ only holds if $\theta_P^*(a_2) < 1$ and if*

$$c_{H,I,N}^2 - c_{H,I,T}^2 + \lambda^{P^2} (-\mu_{H,I,N}\mu_{S,A,N} + \mu_{H,I,T}\mu_{S,A,N} + \mu_{H,I,N}\mu_{S,I,N} - \mu_{H,I,T}\mu_{S,I,T} - \mu_{S,I,N}\mu_{S,I,T} + \mu_{S,I,T}^2) + \lambda^P [c_{H,I,T}(\mu_{S,A,N} - \mu_{H,I,T}) + c_{H,I,N}(\mu_{H,I,N} - \mu_{S,I,T} - \mu_{S,A,N} + \mu_{S,I,N})] > 0. \quad (4.21)$$

(c) *For an agent R that cares about both monetary payoffs and patient health, the CT test rate increasing 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 test rates increase with better technology, due to the improved health outcomes. Theorem 2(b), however, states that an increase in the CT test rate by the primary care physicians only occurs under certain conditions, and may decrease due to improved technology. The reason behind a possible CT test rate decrease is that the monetary payoff for the primary care physician 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, primary care physicians are 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 patients with false positive results is greater than the reduction of patients with false negative results. Meanwhile, unlike radiologists, the monetary payoff for primary care physicians depends not only on imaging tests but also on downstream treatments. A switch from false positives to true negatives decreases the primary care physicians' 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 test rate improves health outcomes, but decrease monetary payoffs. Therefore, higher test rates due to better CT diagnostics only occur if the primary care physician puts a relatively greater emphasis on patient health than on monetary payoffs (large λ^P).

4.3.2 With Incentive

In the scenario with MSSP incentives, the following sequence of events occur: (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 test rates. We assume that agent H chooses fixed incentive sharing percentages α and β for agents P and R, respectively, for the redistribution of the incentive I it receives from CMS. The incentives for the three agents are $I^P = \alpha I$ and $I^R = \beta I$, leaving agent H with $I^H = (1 - \alpha - \beta)I$. We assume $0 \leq \alpha \leq 1$, $0 \leq \beta \leq 1$, $0 \leq \alpha + \beta \leq 1$. We now discuss the agents' optimal decision response with incentives.

4.3.2.1 Stage 2: Agents P and R's decision

Given the decisions by CMS and agent H, agent P chooses the optimal test rate θ_P^{**} to maximize its utility, i.e.,

$$\theta_P^{**} = \arg \max_{\theta_P \in [0,1]} [\Pi^{P1}(\theta_P|a_h) + \lambda^P \cdot B^{P1}(\theta_P|a_h) + I^P]. \quad (4.22)$$

Similarly, agent R chooses

$$\theta_R^{**} = \arg \max_{\theta_R \in [0,1]} [\Pi^{R1}(\theta_P) + \Pi^{R2}(\theta_R) + \lambda^R \cdot B^{R2}(\theta_R|a_h) + I^R]. \quad (4.23)$$

Theorem 3. (a) Agent P's optimal test rate θ_P^{**} is

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

where

$$\tilde{\theta}_P = \frac{\eta\alpha(1 + \gamma_p)c_I + (1 - \eta\alpha)[c_{S,A,N} - \tilde{q}c_{S,I,T} - (1 - \tilde{q})c_{S,I,N}] + \lambda^P[\mu_{S,A,N} - \tilde{q}\mu_{S,I,T} - (1 - \tilde{q})\mu_{S,I,N}]}{(1 - \eta\alpha)(1 - 2\tilde{q})(c_{H,I,T} - c_{H,I,N}) + \lambda^P[(\mu_{S,A,N} - \mu_{H,A,N}) + (1 - \tilde{q})(\mu_{H,I,T} - \mu_{S,I,N}) + \tilde{q}(\mu_{H,I,N} - \mu_{S,I,T})]}; \quad (4.24)$$

(b) Agent R's optimal test rate θ_R^{**} is

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

where

$$\tilde{\theta}_R = \frac{-c_I + \eta\beta(1 + \gamma_p)c_I + \lambda^R\{r \cdot [\mu_{S,A,N} - \tilde{q}\mu_{S,I,T} - (1 - \tilde{q})\mu_{S,I,N}] + (1 - r)[\mu_{H,A,N} - \tilde{q}\mu_{H,I,N} - (1 - \tilde{q})\mu_{H,I,T}]\}}{\lambda^R \cdot r \cdot [\mu_{S,A,N} - \mu_{H,A,N} + (1 - \tilde{q})(\mu_{H,I,T} - \mu_{S,I,N}) + \tilde{q}(\mu_{H,I,N} - \mu_{S,I,T})]}. \quad (4.25)$$

Proof. Taking the derivate of the utility functions of Eq. 4.22 and 4.23, and setting them equal to 0 results in Eq. 4.24 and 4.25. By taking the second derivative, which in both cases is negative, we confirmed that this is the maximum. \square

The optimal test rates θ_P^{**} and θ_R^{**} are again independent from each other. Further, Eqs. 4.24

and 4.25 do not contain the cost benchmark M , which means that a change in the benchmark does not affect the optimal CT test rates. The optimal test rates being independent of cost benchmark M may surprise at first, since one may expect that a higher incentive payment would reduce CT test rates. 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 next.

Corollary 1. *Given incentives and no switch in agent H's investment decision a_h^{**} , agent P's optimal test rate θ_P^{**} is a strictly decreasing function of the sharing percentage α for $\theta_P^{**} \in (0, 1)$. Likewise, agent R's optimal test rate θ_R^{**} is a strictly decreasing function of sharing percentage β for $\theta_R^{**} \in (0, 1)$.*

Proof. See Appendix. □

Corollary 1 confirms the intuition that the larger the sharing percentage, the larger the reduction in test ordering. The reasons why CT test rates are effected by α and β is that the incentive is proportional to the sharing percentages.

Corollary 2. *Given no switch in agent H's investment decision $a_h^* = a_h^{**}$, we always have $\theta_P^{**} \leq \theta_P^*$ and $\theta_R^{**} \leq \theta_R^*$.*

Proof. See Appendix. □

Corollary 2 confirms that MSSP incentives can reduce the number of CT tests ordered by primary care physicians and radiologists. Therefore, it is an effective mechanism to address CT scan overuse that results from an FFS payment scheme.

4.3.2.2 Stage 1: Agent H's decision

Agent H chooses the optimal investment decision a_h^{**} and the optimal sharing percentages α^{**} and β^{**} to maximize its utility. Agent H's UMP is

$$\max_{a_h, \alpha, \beta} U^H(a_h, \alpha, \beta) = \Pi^H(a_h) + \lambda^H \cdot B^H + (1 - \alpha - \beta)I \quad (4.26)$$

$$\begin{aligned} \text{s.t. } \quad & 0 \leq \alpha \leq 1, \\ & 0 \leq \beta \leq 1, \\ & 0 \leq \alpha + \beta \leq 1. \end{aligned}$$

In the analysis of Stage 2 (Section 4.3.2.1), we had just shown that the cost benchmark M does not affect the optimal test rates θ_P^{**} and θ_R^{**} directly. However, the analysis of Stage 1 with UMP 4.26 shows that M affects agent H's optimal decisions a_h^{**} , α^{**} and β^{**} . Given that these decision variables in turn affect test rates θ_P^{**} and θ_R^{**} , we now 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 4.26 is a constrained optimization problem with numerous parameters and nonlinearities; hence closed-form solutions for a_h^{**} , α^{**} and β^{**} cannot be derived. Nevertheless, the global optima can be determined with low computational effort for concrete parameter values. In the following section, we provide numerical solutions to agent H's UMP and discuss how the cost benchmark M affect agent H's decisions and the optimal test rates θ_P^{**} and θ_R^{**} .

4.4 Numerical analysis

Our numerical analysis is based on parameter values, which are listed in the Appendix. For all calculations, in particular for solving the UMPs, we used the technical computing software Mathematica®. We follow the backward induction principle discussed in Section 4.3, i.e., we first calculate agents P and R's optimal decision response (Stage 2), followed by agent H's optimal decision (Stage 1). In the first part of our analysis, we investigate the equilibrium solutions for a fixed cost benchmark. Thereafter, we will vary the benchmark to analyze its effect.

Table 4.2: Equilibrium results of base case

		No incentive	With incentive	No incentive	With incentive
		<u>Investment</u> (a_1)		Status quo (a_2)	
θ_P	Test rate by P	<u>0.952</u>	<u>0.942</u>	0.947	0.941
θ_R	Test rate by R	<u>0.738</u>	<u>0.542</u>	0.700	0.503
α	Sharing % for P	-	0.076	-	0.048
β	Sharing % for R	-	0.365	-	0.349
U^H	H's utility	13961	14037	13833	13930
U^P	P's utility	9963	9972	9665	9672
U^R	R's utility	5262	5283	5219	5249

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

We assume the cost benchmark to be $M=3700$. For this value, we determine the agents' optimal decisions and their utility values. We compare the no incentive scenario with the MSSP incentive scenario. The results are summarized in Table 4.2. The agents' optimal decision variable values 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. Taking a closer look at the no incentive scenario, we see that agent H prefers to make the investment (decision a_1) since $U^{H*}(a_1) = 13961 > U^H(a_2) = 13833$. In this 2-stage game, agent H's utility values depend on agent P and R's optimal decision response to agent H's decision. Agent P and R's CT test rates are higher with agent H's CT scanner investment compared to the status quo; $\theta_P^* = 0.952 > 0.947$ and $\theta_R^* = 0.738 > 0.700$. Agents P and R also prefer that agent H makes the investment since their utility values are higher ($9963 > 9665$, $5262 > 5219$), though this is not a necessary condition for the equilibrium.

In the scenario with incentives, the results are similar: agent H makes a CT scanner investment and the resulting test rates are higher compared to the status quo with $\theta_P^{**} = 0.942 > 0.941$ and $\theta_R^{**} = 0.542 > 0.503$. When comparing the incentive scenario with the no incentive

scenario, we see that incentives lead to lower CT test rates; $0.942 < 0.952$ (agent P) and $0.542 < 0.738$ (agent R). Agent H shares a part of the MSSP incentive with the agents P and 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% of the MSSP incentive 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).

We can also analyze how the agents' two objective function attributes, money and health, affect the test rates. For 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 money, their test rate would be 1, as shown in Lemma 2. If they only cared about health benefits for the patient, their rate would be lower; $\theta_P^{h*} = 0.900 < 0.952$ and $\theta_R^{h*} = 0.500 < 0.738$, given CT scanner investment by agent H. Without investment, the health-maximizing test rates reduce even further; $\theta_P^{h*} = 0.890 < 0.947$ and $\theta_P^{h*} = 0.450 < 0.700$.

As a final step, we perform a sensitivity analysis to investigate the circumstances under which agent H would change its investment decision. We vary one model parameter at time to determine the transition point of parameter values at which agent H would switch from investment (a_1) to status quo (a_2). Table 4.3 summarizes the results.

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 (i.e., status quo) decision by agent H. Comparing the incentive with the no incentive scenario, we can see that incentives make an investment less attractive or likely, since $307 < 328$. The same effect can be observed for maintenance costs $c^H(s_1)$, cost impact factor γ_c , and, in opposite direction, for diagnostic accuracy δ . For the other parameters listed in Table 4.3, no transition point existed in our numerical example. In addition to the insights on sensitivity of the decision with respect to the various parameters, the analysis also showed that incentives reduce the attractiveness of a CT scanner investment for agent H; i.e., incentives reduce the CT scanner investment propensity of hospitals.

Table 4.3: Sensitivity analysis of agent H's optimal investment decision

Parameter	Parameter description	Initial value	Transition point	
			No incentive	With incentive ($M=3700$)
k_1	Investment cost	200	328	307
$c^H(s_1)$	Maintenance cost	10	193	162
γ_c	Cost impact from agent R on H	3	13.7	8.6
γ_p	Revenue impact from agent R on H	3.5	None	None
δ	Diagnostic accuracy	0.05	0.031	0.033
$\Pr(s_1 a_1)$	Probability of high maintenance cost given the decision to invest	0.9	None	None

4.4.2 Optimal Incentive Distribution Mechanism: Effect of Cost Benchmark M

In this section, 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 4.4 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, CT scanner 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 of this result is that by providing higher incentives through less stringent cost benchmarks, CMS makes medical technology investments less attractive to hospitals, i.e., the investment propensity is reduced.

While the investment decision remains the same for varying M , the incentive distribution within the ACO changes. Agent H decides on the incentive distribution, and the optimal values for varying M are shown in Figure 4.5.

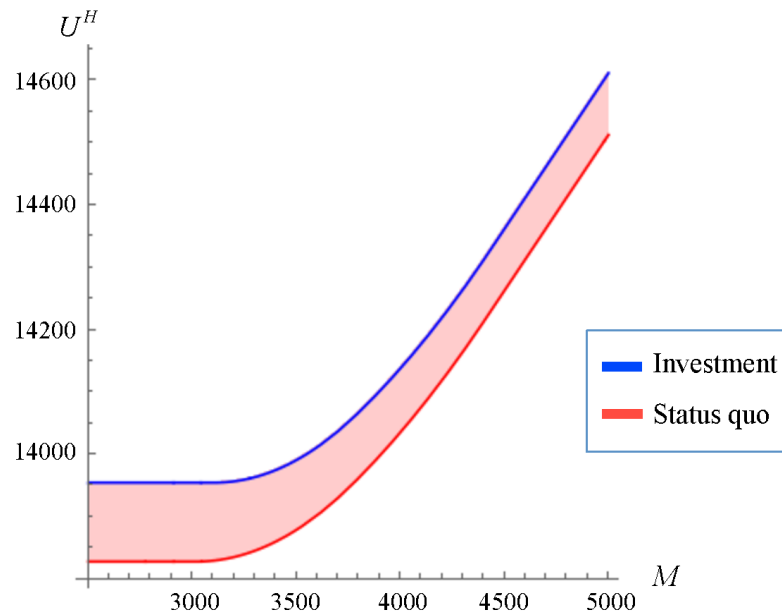


Figure 4.4: The investment propensity of agent H for varying cost benchmark M

In Figure 4.5, we can distinguish between three areas that exhibit 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 rate reduction. In contrast, for a large M and thus high MSSP incentives for the ACO (area c), agent H benefits most from keeping the incentive entirely to itself. Incentivizing agents P and R is not attractive. In area b, the incentive distribution lies in between the two extremes.

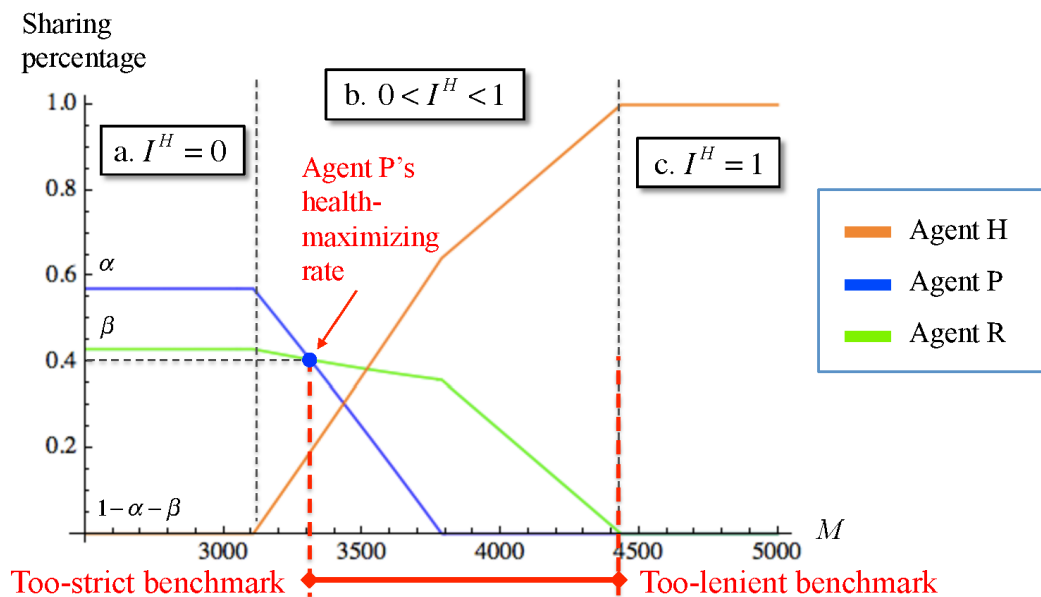


Figure 4.5: Benchmark affects the optimal sharing percentages

In choosing M , the goal of CMS should be to provide incentives that result in a CT test rate that maximizes patient health. As we had shown in earlier results, the health-maximizing CT test rates are $\theta_P^{*h} = 0.900$ and $\theta_R^{*h} = 0.500$. For $M = 3300$, the patient health-maximizing and agent P's utility-maximizing CT test rate of $\theta_P^{**} = \theta_P^{*h} = 0.900$ is achieved; marked by a blue dot in Figure 4.5. Higher M and thus more incentives paid out by CMS, reduces the sharing percentage α^{**} , and with it the CT test rate increases. Higher CMS incentives resulting in higher CT test rate is paradoxical, but can be explained by the incentive redistribution effect within the ACO. Too low incentives, $M < 3300$, result in too low CT test rates, and are undesirable from a patient health perspective. The test rate of agent R, θ_R^{**} , stays above the health-maximizing rate of $\theta_R^{*h} = 0.500$ over the entire range of M .

In choosing M , CMS also needs to consider the willingness of the ACO and its members – agents H, P and R – 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 of these findings is that CMS may have to set a higher cost benchmark than

Table 4.4: CMS's benchmarks, utility decompositions, and participation constraints

M	Overall health care costs (Billings)	MSSP incentive	Net cost for CMS	Population health benefit	Agents' willingness to participate in ACO as M increases
3000	3230.59	-115.29	3115.29	1388.13	
3100	3230.59	-65.29	3165.29	1388.13	
3200	3265.43	-32.71	3232.71	1388.29	
3300	3302.34	-1.17	3301.17	1388.35	H's participation starts
3400	3339.20	30.40	3369.60	1388.29	
3500	3376.01	61.99	3438.01	1388.10	P's participation starts
3600	3412.77	93.62	3506.38	1387.79	R's participation starts
3700	3449.50	125.30	3574.80	1387.30	
3800	3485.66	157.17	3642.83	1386.82	
3900	3518.99	190.51	3709.49	1386.32	
4000	3552.32	223.84	3776.16	1386.32	
No incentive	3696.50	0	3696.50	1384.00	

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 would make agent H just willing to participate, while agents P and R would be worse off compared to the no incentive scenario.

In Table 4.4, we have summarized the system-wide health care costs, i.e., agents' billings to CMS, the MSSP incentive, CMS' net costs and the 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 an $M = 3600$ may be necessary to ensure the participation of all stakeholders. Whether CMS prefers to even offer the incentive program under these circumstances, depends on their willingness to pay for health, λ^{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 higher CT test rates. 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 careful analysis before setting the cost benchmark. Giving in to the demands of ACOs to raise the cost benchmark, would not only increase costs, but could hurt the patients.

4.5 Conclusions

In this chapter, we developed a multi-level decision-making model with a hierarchical game structure, and evaluated the effects of reimbursement and shared savings incentives on health care decision-making within the scope of radiology and ACOs. We used multiscale decision theory to capture the multi-level interactions and interdependencies of four decision makers: CMS (payer), 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 subgame perfect Nash equilibrium concept. We showed that in the scenario without incentive, i.e., a fee-for-service payment system, both primary care physicians and radiologists are incentivized to order and perform excessive imaging tests. We further showed that the MSSP incentives can effectively decrease the CT test rates, and reduces hospital's propensity to purchase new and expensive CT scanner devices.

Using a case study with exemplary data, 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, not sharing them with their physician members. In this case, the MSSP has no effect on CT test rate reduction. When reducing the cost benchmark below a certain threshold, hospitals begin to share the MSSP incentive with physicians. The

greater the sharing rate, the stronger the motivation by the physicians to reduce test rates. Under certain conditions, the cost benchmark can be set just right so it reduces CT test rate to the patient health-maximizing rate. Further reducing the cost benchmark can result in CT test underutilization.

In setting the cost benchmark, CMS also needs to consider the willingness of the ACO to participate in the program. Our numerical example illustrated a case where CMS needed to set the cost benchmark higher than optimal from a patient health perspective, since otherwise ACO members would not have participated in MSSP. A win-win-win-win situation for CMS, ACO, physicians and patients is possible with MSSP, but depends on the model parameters.

Our analysis shows the importance of a model-driven and data-driven evaluation of MSSP for setting one of its key parameters, the cost benchmark. The current practice of ACOs trying to negotiate for a higher, more lenient cost benchmark, may lead to higher health care costs and worse health outcomes. However, a too low and too stringent cost benchmark can result in too low CT test rates, and may jeopardize the willingness of the ACO to participate in the first place.

The following limitations of our study should be considered. We assumed a single payer (CMS) with a single incentive program (MSSP), which over-simplifies the payment structures that both providers and payers experience. Further, we assumed that each agent in our model seeks to maximize the two-attribute utility function consisting of monetary payoff and patients health benefits. In practices, agents may care about a wider spectrum of attributes in their technology usage and investment decisions, such as fear of malpractice litigation, patient preferences, hospital reputation, budget constraint, etc. Lastly, we analyzed a non-repeated game, which limits the model's capabilities in capturing the dynamic evolution of patient health and the temporal impact of incentives on health care costs and quality.

Despite these limitations, our paper provides important insights from a health policy perspective as it considers the decision interdependencies of four stakeholders, and shows the resulting decision complexities. By further advancing this model, including calibrating it

with real-world data, the MSDT modeling approach has the potential to directly inform stakeholder decisions, such as what the optimal cost benchmark for CMS would be.

Chapter 5

Incentives in Chronic Disease Management: A Game Theoretic Framework

5.1 Introduction

Chronic diseases, such as hypertension, diabetes mellitus and coronary heart disease, account for more than \$1 trillion of healthcare costs and lost productivity in the US [127]. Heart disease, in particular, is the diagnostic group with the highest healthcare costs, estimated to reach \$46.8 billion by 2015, and is responsible for one in six deaths [128]. The prevalence and costly effects of chronic disease can often be prevented, delayed or mitigated [129]. Empirical studies found that chronic disease prevention and proactive management significantly reduce acute care utilization [130, 131, 132]. For example, regular primary care office visits alone can reduce hospital admissions by 46% and emergency department visits by 38% [133]. Primary care, in particular for at-risk patients, is essential in detecting diseases at their early stages and for initiating timely clinical interventions. Moreover, health risk factors resulting from

patient behaviors, such as diet, exercise and smoking, can be reduced through physicians' counseling and patients' self-management [134].

Patients and payers are the immediate beneficiaries of chronic disease management. Patients experience an increase in their quality of life and benefit financially [135]. For example, evidence indicates that health promoting behavior such as regular physical activity is associated with decreased coronary heart disease (CHD) risks [136, 137]. Meanwhile, payers could also benefit from significant cost reductions. The average costs for hospital stay due to heart disease is \$16,500 in 2010 [138]. Evidence from Medicare demonstration programs shows that endeavors such as patient education and targeting interventions to risk groups could reduce chronic disease hospitalization by 17-24% and total Medicare costs by 10-20% [139].

Despite the significant benefits for multiple parties, chronic disease prevention and management is underutilized in the US [140]. At the provider level, physicians focus primarily on acute care [23]. Time constraints and financial pressures to see more patients limit physicians' ability to perform comprehensive consultation services that focus on health maintenance issues [24]. One of the misaligned incentives here is that preventive care and primary care services are underpaid in comparison with acute care activities. On the other hand, patients are not seeking primary care or performing health promoting behavior proactively. Behavioral hurdles, including time, psychological costs and not experiencing immediate benefits from primary care or lifestyle change, are disincentives for patients to manage their disease conditions effectively.

Better payment and incentive structures have been identified by healthcare experts as a key mechanism for curbing costs while improving care [4, 5]. Incentives need to be re-aligned to promote higher primary care utilization and healthier lifestyles. At the patient level, monetary incentives can enhance customers' purchasing behavior by reducing costs and/or increase disposable income. Studies found that financial rewards can promote customers' smoking cessation and the control of cholesterol level [141, 142]. At the provider level, value- and outcome-based reimbursements are being introduced to promote cost-effective

care and care coordination between physicians and patients. How to incentivize physicians to optimally allocate clinical efforts, thereby promoting the delivery of primary care and improving health outcomes, is a question that needs to be addressed.

The objectives of this research are to identify and design healthcare incentives that lead to better chronic disease management. We consider patients' lifestyle and primary care decisions, accounting for their responses to financial incentives and other behavioral factors based on the health belief model (HBM) [115]. We also consider the allocation of effort by primary care physicians during clinical encounters, recognizing physicians' intrinsic and extrinsic, financial and non-financial motivations. The patient and physician level decisions are further coupled through stochastic game approach to formulate a two-level, multi-period model that captures the dynamic and interdependent components of incentive mechanisms.

5.2 Chronic Disease Management as Stochastic Games

Consider the chronic disease management problem as a two-level, multiple-period decision making process. At the patient level, an individual patient (*agent PA*) chooses decisions of primary care engagement and lifestyles. At the physician level, a primary care physician (*agent PCP*) decides the effort spent in each clinical encounter. Meanwhile, the decisions and outcomes of both agents are affected by the underlying incentive mechanisms of the health care system. In reality, there can be more than one patient seeing a primary care physician and more than one physician treating a patient at the same time. In this study, we limit our attention to one-on-one interactions between a single patient and a single physician. The two-player model is sufficient to answer how each agent should respond to the other player in a game theoretical setting. The model can also answer such question in a homogeneous multi-patient (or multi-physician) situation. Any consideration of heterogeneous players can be an extension for future studies.

5.2.1 Stochastic Game Model

We first introduce the general model structure of a stochastic game. We then apply the model to the chronic disease management problem and illustrate how to define patient states, agents' actions, state transition probabilities, and reward functions.

We formulate a discrete-time, infinite-horizon, discounted stochastic model, represented using a 6-tuple: $\Gamma = \{S, A_s^{PA}, A_s^{PCP}, P, R^{PA}, R^{PCP}\}$, where:

- $S := \{s_1, \dots, s_i, \dots, s_N\}$ is the patient state space;
- $A^{PA} := \{a_1^{PA}, a_2^{PA}, \dots, a_{M^{PA}}^{PA}\}$ is the action space of agent PA. The action set for agent PA in state $s_i \in S$ is a subset of A^{PA} , i.e., $A_{s_i}^{PA} \subseteq A^{PA}$ and $\bigcup_{i=1}^N A_{s_i}^{PA} = A^{PA}$;
- $A^{PCP} := \{a_1^{PCP}, a_2^{PCP}, \dots, a_{M^{PCP}}^{PCP}\}$ is the action space of agent PCP. The action set for agent PCP in state $s_i \in S$ is a subset of A^{PCP} , i.e., $A_{s_i}^{PCP} \subseteq A^{PCP}$ and $\bigcup_{i=1}^N A_{s_i}^{PCP} = A^{PCP}$;
- $P := S \times A_{s_i}^{PA} \times A_{s_i}^{PCP}$ is the transition probability matrix;
- $R^{PA} := S \times A_{s_i}^{PA}$ is the reward function for agent PA;
- $R^{PCP} := S \times A_{s_i}^{PCP}$ is the reward function for agent PCP.

The game is played as follows. At any discrete time epoch $t = 1, 2, \dots$, given the current state $s_t \in S$, agent PA chooses an action $a_{s_t}^{PA}$ from A^{PA} and agent PCP chooses an action $a_{s_t}^{PCP}$ from A^{PCP} . Based on the current state s_t and both agents' choices of actions $a_{s_t}^{PA}$ and $a_{s_t}^{PCP}$, each agent receives a reward according to the reward function R^{PA} and R^{PCP} . The game then moves to a new state $s_{t+1} \in S$ at the next time epoch, with transition probability $\Pr(s_{t+1}|s_t, a_{s_t}^{PA}, a_{s_t}^{PCP})$. Each agent calculates the accumulated reward from each time period. Due to the infinite time horizon of the game, we assume that each agent maximizes its long-run discounted accumulated reward. The discount factor β is used to denote the weight agents assign to future rewards.

5.2.2 Patient State

The patient state s_i is defined by three dimensions: health status h , current lifestyle l , and healthcare setting k . Specifically, health status is a vector of values $\{1, 2, \dots, H, H+1\}$, where $h = 1, \dots, H$ represents *chronic conditions* and $h = H + 1$ represents an *acute episode*. We assume a complete ordering of health status, with $h=1$ representing the best health status of the chronic condition and $h = H$ representing the worst health status of the chronic condition. Health status $h = H + 1$ represents an acute episode where a patient has to be hospitalized. Current lifestyle l refers to various lifestyle characteristics such as diet, smoking, and active level, and can be generalized as either a healthy, beneficial lifestyle (B) or non-beneficial, unhealthy, lifestyle (Nb). Possible healthcare settings k are home (Hm), PCP's office (Po) and hospital (Hs).

For example, $s = (1, B, Hm)$ means the patient is at home, experiencing the least severe chronic symptoms and living a lifestyle that is beneficial to health, whereas $s = (2, Nb, Po)$ means that the patient's health is one-stage worse, the patient has a lifestyle that is not beneficial to health, and is at the PCP's office seeking care. We assume that agent PA will only be hospitalized in acute episode, not in chronic conditions; hence the following states can be ruled out from our model: $(H + 1, l, Hm), \forall l$; $(H + 1, l, Po), \forall l$; and $(h, l, Hs), h = 1, \dots, H, \forall l$.

5.2.3 Actions

An action pair by agent PA and agent PCP causes the system to move from one state to another subject to transition probabilities. In this model, we assume that for all the states with a healthcare setting of Hm , agent PA is the sole decision maker, or controller, that influences the transition probabilities; whereas for all the states with a healthcare setting of Po , only agent PCP makes decisions and controls the transitions.

Denote agent PA's action set as $A_{(h,l,Hm)}^{PA}$ and agent PCP's action set as $A_{(h,l,Po)}^{PCP}$. Specifically,

when $s = (h, B, Hm)$, with $h = 1, \dots, H$, agent PA makes two kinds of decisions: (1) *maintain* the current healthy lifestyle vs. *relapse* into an unhealthy lifestyle and (2) remain at *home* or visit the *PCP* at the next time epoch. The action set of agent PA is thus

$$A_{(h,B,Hm)}^{PA} = \{(maintain, home), (maintain, PCP), (relapse, home), (relapse, PCP)\}.$$

When $s = (h, Nb, Hm)$, with $h = 1, \dots, H$, agent PA decides (1) *switch* to a healthy lifestyle vs. lifestyle *status quo* and (2) remain at *home* or visit the *PCP* at the next time epoch. The action set of agent PA is thus

$$A_{(h,Nb,Hm)}^{PA} = \{(switch, home), (switch, PCP), (status quo, home), (status quo, PCP)\}.$$

For any other state s' , agent PA's action set is empty, meaning that the agent has no action to choose from. We denote the agent's inaction as ϕ . We have $A_{s'}^{PA} = \{\phi\}$.

Next, we define the action sets for agent PCP. When $s = (h, l, Po)$, with $h = 1, \dots, H$ and $\forall l$, agent PCP chooses between expending *high* effort or *low* effort on the clinical encounter with the patient. The action set of agent PCP is denoted as $A_{(h,l,Po)}^{PCP} = \{high, low\}$. For any other state s'' , agent PCP's action set is empty, i.e., $A_{s''}^{PCP} = \{\phi\}$.

Note that when $s = (H + 1, l, Hs)$, $\forall l$, the patient is hospitalized, and thus neither agent PA nor agent PCP makes decisions, i.e., $A_{(H+1,l,Hs)}^{PA} = A_{(H+1,l,Hs)}^{PCP} = \{\phi\}$.

5.2.4 State Transition Probabilities

The transition probability $\Pr(s'|s, a_i^{PA}, a_j^{PCP})$ is influenced by the current state s and agents' actions a_i^{PA} and a_j^{PCP} . Given the three dimensions of patient state, we assume that

$$\Pr[(h', l', k') | (h, l, k), a_i^{PA}, a_j^{PCP}] = \mathcal{H}(h'|h, a_i^{PA}, a_j^{PCP}) \cdot \mathcal{L}(l'|l, a_i^{PA}, a_j^{PCP}) \cdot \mathcal{K}(k'|k, a_i^{PA}, a_j^{PCP}, h'), \quad (5.1)$$

where $\mathcal{H}(h'|h, a_i^{PA}, a_j^{PCP})$ is the probability that the patient's health status will be h' at time

$t + 1$ given the health status h and actions at time t ; $\mathcal{L}(l'|l, a_i^{PA}, a_j^{PCP})$ is the probability that the patient's lifestyle will be l' at time $t + 1$ given the lifestyle l and actions at time t ; and $\mathcal{K}(k'|k, a_i^{PA}, a_j^{PCP}, h')$ is the probability that the healthcare setting will be k' at time $t + 1$ given the healthcare setting k and actions at time t , and the health status h' at time $t + 1$. We assume that the transitions among health status and the transitions among lifestyle are independent, whereas the transitions among healthcare setting are dependent on the transitions among health status. Next, we explain the transition probabilities \mathcal{H} , \mathcal{L} , \mathcal{K} in details.

5.2.4.1 Health status

Both the current lifestyle and clinical interventions affect the transitions among health status. In agent PA's controlling states, the health status of the next time period is influenced by the current lifestyle, and it transitions according to the transition probability matrix (TPM) $\mathcal{H}_B(h'|h)$ if the current lifestyle is B , or according to TPM $\mathcal{H}_{Nb}(h'|h)$ if the current lifestyle is Nb . Mathematically,

$$\mathcal{H}[h'|(h, B, Hm), a_i^{PA}, \phi] = \mathcal{H}_B(h'|h),$$

$$\mathcal{H}[h'|(h, Nb, Hm), a_i^{PA}, \phi] = \mathcal{H}_{Nb}(h'|h),$$

with $h = 1, \dots, H$, $\forall h', a_i^{PA}$, and

$$\mathcal{H}_B(h'|h) = \begin{matrix} & \begin{matrix} 1 & 2 & \dots & H & H + 1 \end{matrix} \\ \begin{matrix} 1 \\ 2 \\ \vdots \\ H \end{matrix} & \begin{pmatrix} p_{B11} & p_{B12} & \dots & p_{B1H} & p_{B1(H+1)} \\ p_{B21} & p_{B22} & \dots & p_{B2H} & p_{B2(H+1)} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ p_{BH1} & p_{BH2} & \dots & p_{BHH} & p_{BH(H+1)} \end{pmatrix} \end{matrix},$$

$$\mathcal{H}_{Nb}(h'|h) = \begin{array}{c} \\ \\ \\ \\ \\ \\ \\ \end{array} \begin{array}{c} 1 \\ 2 \\ \vdots \\ H \end{array} \begin{array}{ccccc} 1 & 2 & \dots & H & H+1 \\ \left(\begin{array}{ccccc} p_{Nb11} & p_{Nb12} & \dots & p_{Nb1H} & p_{Nb1(H+1)} \\ p_{Nb21} & p_{Nb22} & \dots & p_{Nb2H} & p_{Nb2(H+1)} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ p_{NbH1} & p_{NbH2} & \dots & p_{NbHH} & p_{NbH(H+1)} \end{array} \right) \end{array}.$$

In agent PCP's controlling states, the health status transitions according to TPM $\mathcal{H}_{Po}(h'|h)$, reflecting the influence of primary care. That is,

$$\mathcal{H}[h'|h, l, Po, \phi, a_j^{PCP}] = \mathcal{H}_{Po}(h'|h),$$

with $h = 1, \dots, H$, $\forall h', l, a_j^{PCP}$, and

$$\mathcal{H}_{Po}(h'|h) = \begin{array}{c} \\ \\ \\ \\ \\ \\ \\ \end{array} \begin{array}{c} 1 \\ 2 \\ \vdots \\ H \end{array} \begin{array}{ccccc} 1 & 2 & \dots & H & H+1 \\ \left(\begin{array}{ccccc} p_{Po11} & p_{Po12} & \dots & p_{Po1H} & p_{Po1(H+1)} \\ p_{Po21} & p_{Po22} & \dots & p_{Po2H} & p_{Po2(H+1)} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ p_{PoH1} & p_{PoH2} & \dots & p_{PoHH} & p_{PoH(H+1)} \end{array} \right) \end{array}.$$

During an acute episode where neither agent is the controller, the health status transitions according to TPM $\mathcal{H}_{Hs}(h'|h)$, reflecting the influence of acute care. That is,

$$\mathcal{H}[h'|H+1, l, Hs, \phi, \phi] = \mathcal{H}_{Hs}(h'|H+1),$$

with $\forall h', l$ and

$$\mathcal{H}_{Hs}(h'|H+1) = H+1 \begin{array}{ccccc} 1 & 2 & \dots & H & H+1 \\ \left(\begin{array}{ccccc} p_{Hs(H+1)1} & p_{Hs(H+1)2} & \dots & p_{Hs(H+1)H} & p_{Hs(H+1)(H+1)} \end{array} \right) \end{array}.$$

The elements in each row of the TPMs sum up to 1.

5.2.4.2 Lifestyle

Both agent PA's lifestyle choice and agent PCP's effort level influence the lifestyle transitions. We assume that agent PA's action deterministically influences the lifestyle of the next time period. Mathematically,

$$\mathcal{L}[B|(h, B, Hm), (maintain, \cdot), \phi] = 1,$$

$$\mathcal{L}[Nb|(h, B, Hm), (relapse, \cdot), \phi] = 1,$$

$$\mathcal{L}[B|(h, Nb, Hm), (switch, \cdot), \phi] = 1,$$

$$\mathcal{L}[Nb|(h, Nb, Hm), (status\ quo, \cdot), \phi] = 1,$$

with $h = 1, \dots, H$.

Meanwhile, we assume that agent PCP's effort level stochastically affects patient's lifestyle of the next time period. This assumption is based on the construct *cues to action* in HBM theory [115]. If the current lifestyle is Nb , a *high* effort by agent PCP may trigger the patient to stop the unhealthy lifestyle and adopt the recommended healthy lifestyle in the next period, leading to lifestyle B with probability $p_{h,B}$; and the probability of the patient disregarding the PCP's recommendation and continuing the current non-beneficial lifestyle in the next period is $p_{h,Nb} = 1 - p_{h,B}$. If a *low* effort is chosen, the probability of continuing with Nb in the next period is $p_{l,Nb}$, and the probability of transferring to B in the next period is $p_{l,B} = 1 - p_{l,Nb}$. When the current lifestyle is B , the lifestyle of the next period will remain B with certainty regardless of agent PCP's action. Mathematically,

$$\mathcal{L}[B|(h, B, Po), \phi, a_j^{PCP}] = 1, \text{ with } h = 1, \dots, H \text{ and } \forall a_j^{PCP};$$

$$\mathcal{L}[B|(h, Nb, Po), \phi, high] = p_{h,B},$$

$$\mathcal{L}[Nb|(h, Nb, Po), \phi, high] = 1 - p_{h,B},$$

$$\mathcal{L}[B|(h, Nb, Po), \phi, low] = 1 - p_{l,Nb},$$

$$\mathcal{L}[Nb|(h, Nb, Po), \phi, low] = p_{l,Nb},$$

with $h = 1, \dots, H$.

During an acute episode, both agents are inactive. Hence, we assume that the patient's lifestyle remains unchanged.

5.2.4.3 Healthcare setting

The healthcare setting of the next time period depends on the current state, agents' actions, as well as on the health status of the next time period. Specifically, in agent PA's controlling states, agent PA chooses whether to stay at home or have primary care in the next time period. Thus,

$$\mathcal{K}[Hm|(h, l, Hm), (\cdot, home), \phi, h'] = 1,$$

$$\mathcal{K}[Po|(h, l, Hm), (\cdot, PCP), \phi, h'] = 1,$$

with $h, h' = 1, \dots, H$ and $\forall l$.

In agent PCP's controlling states, we assume that the healthcare setting deterministically transitions to Hm after a clinical encounter in the PCP's office. That is,

$$\mathcal{K}[Hm|(h, l, Po), \phi, a_j^{PCP}, h'] = 1,$$

with $h, h' = 1, \dots, H$ and $\forall l, a_j^{PCP}$.

Additionally, in any health status $h = 1, \dots, H, H + 1$, the system may transition to (or stay in) an acute episode $h = H + 1$, as described by TPMs \mathcal{H}_B , \mathcal{H}_{Nb} , \mathcal{H}_{Po} , and \mathcal{H}_{Hs} . When an

acute event occurs, the patient will be immediately hospitalized to receive acute care. That is,

$$\mathcal{K}[Hs|(h, l, k), a_i^{PA}, a_j^{PCP}, H + 1] = 1,$$

with $\forall h, l, k, a_i^{PA}, a_j^{PCP}$.

When an acute event ends, i.e., the patient recovers, the healthcare setting will transition back to Hm :

$$\mathcal{K}[Hm|(H + 1, l, k), \phi, \phi, h'] = 1,$$

with $h' = 1, \dots, H$ and $\forall l, k$.

5.2.4.4 An Illustration

The final state transition probabilities is an aggregation of the transitions of the three state dimensions and can be calculated using Eq. 5.1. A complete table of the state transition probabilities can be found in Appendix B.1.

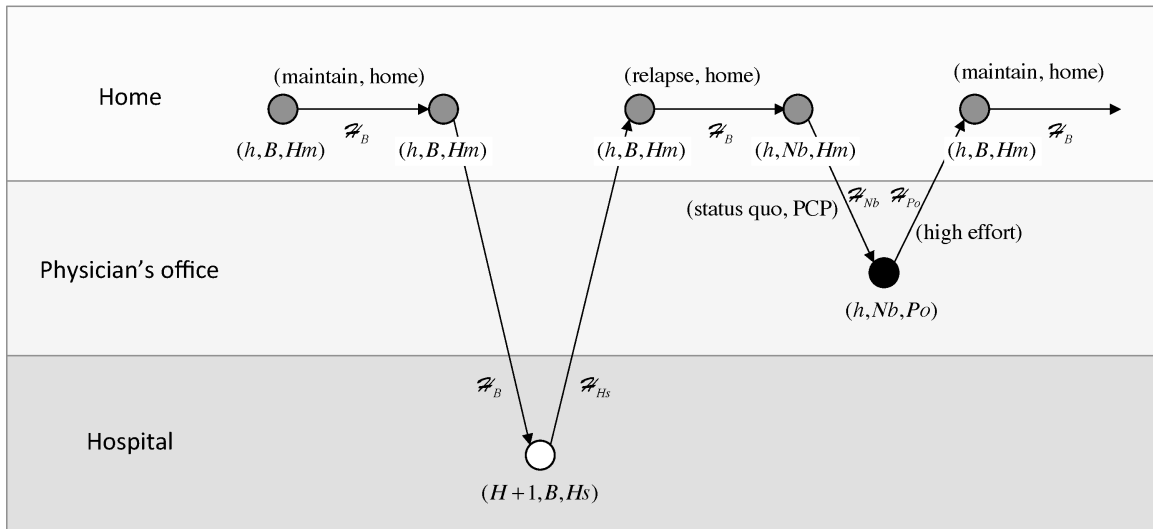


Figure 5.1: A graphical illustration of the system transitions

Figure 5.1 provides an example that illustrates the transitions of the system. Each arrow

represents a state transition, labeled with actions and a transition probability. In our model, agent PA controls the states marked by the grey circle where agent PCP is inactive, while agent PCP controls the states marked by the black circle where agent PA is inactive. Note that in the states $(H + 1, l, Hs)$, marked by the white circle, both agents are inactive and make no decision.

In Figure 5.1, a patient that starts with a state (h, B, Hm) , for example, chooses the action $(maintain, home)$ and may transition to the state (h, B, Hm) subject to the TPM \mathcal{H}_B . Next, an acute episode may happen subject to the TPM \mathcal{H}_B . After the hospitalization event, the patient may transition back to the healthcare setting Hm subject to the TPM \mathcal{H}_{Hs} . At any time epoch with a healthcare setting Hm , the patient can choose to have primary care and move to the setting Po . Then, a *high* effort action from the physician may help the patient switch from lifestyle Nb to B in the next time epoch with probability $p_{Pohh'} \cdot p_{h,B}$.

5.2.5 Rewards

There are rewards associated with both agents' actions and the current system state, realizing at each time epoch. Agent PA's reward is comprised of three components: health utility, action cost, and payment. We further assume that these reward components are additive in the reward functions. Specifically, health utility depends on the current health status h , denoted as $u^{PA}(h)$. Action cost is a monetary representation of the psychological cost of taking actions. We assume that *maintaining* a B lifestyle incurs a maintaining cost of c_1^{PA} ; *switching* from lifestyle Nb to B incurs a switching cost of c_2^{PA} ; and relapsing from lifestyle B to Nb or staying in lifestyle Nb requires a cost of 0. Additionally, a primary care visit with high PCP effort results in a patient payment of m_1^{PA} , whereas low effort result in a patient payment of m_2^{PA} . An acute care event results in a patient payment of m_{Hs}^{PA} .

Agent PCP's reward is comprised of two components: reimbursement and disutility of adverse health outcomes. Reimbursement represents physician's revenue minus cost (time, effort, etc.), and is n_1^{PCP} and n_2^{PCP} for high effort and low effort, respectively. Additionally,

agent PCP also cares about patient health outcome. Since a complete history of patient health status is not observable to the physician, we assume that only an acute episode affects agent PCP’s reward. Let u_{Hs}^{PCP} be the health disutility for agent PCP whenever an acute event happens to the patient. A complete list of agent PA and PCP’s reward functions can be found in Appendix B.2.

Depending on agents’ rewards, a stochastic game can be categorized as a *zero-sum* game if two agents have strictly opposite rewards in each state and period of the game, or as a *general-sum* game if such condition does not hold. The two kinds of games requires different equilibrium concepts and solution methods. Since patients and physicians are not a “rivalry”, our model formulation is a general-sum game. Mathematically,

$$r^{PA}(s, a_i^{PA}, a_j^{PCP}) \neq -r^{PCP}(s, a_i^{PA}, a_j^{PCP}), \text{ for some } s, a_i^{PA}, a_j^{PCP}.$$

Next, we illustrate the equilibrium concept and solution method based on the general-sum game structure.

5.3 Nash Equilibrium

In this section, we introduce the concept of the Nash equilibrium (NE) in a general stochastic game, and then examine our model formulation and identify its specific game structures. Based on the structural properties, we develop a solution algorithm to find the NEs of our model.

5.3.1 Strategies and NE Strategies

We revisit the general model for stochastic games. The agents partly control the game by taking actions, thereby receiving immediate reward based on the state transitions. Define a *strategy* chosen by a agent as a block row vector $\mathbf{f} = [\mathbf{f}(s_1), \dots, \mathbf{f}(s_i), \dots, \mathbf{f}(s_N)]$. Each

block is $\mathbf{f}(s) = [f(s, a_1), f(s, a_2), \dots, f(s, a_M)]$, with $\sum_{j=1}^{M(s)} f(s, a_j) = 1$. Each element in the block, $f(s, a_j)$, represents the probability that the agent chooses an action $a_j \in A_s$ when in state s . Let (\mathbf{f}, \mathbf{g}) denote the strategy pair that agent 1 and agent 2 choose. Let s_t be the state at time t and r_t^i be agent i 's reward at time t . We have the expected accumulated reward of agent i under the strategy pair (\mathbf{f}, \mathbf{g}) and the discount factor β as a vector $\mathbf{v}_{f,g}^i = [v_{f,g}^i(s_1), v_{f,g}^i(s_2), \dots, v_{f,g}^i(s_N)]$, where

$$\mathbf{v}_{f,g}^i(s) = E_{s,f,g}[r_t^i + \beta r_{t+1}^i + \beta^2 r_{t+2}^i + \dots + \beta^H r_{t+H}^i | s_t = s] = \sum_t^{t+H} \beta^t E_{s,f,g}(r_t^i). \quad (5.2)$$

Here, $\mathbf{v}_{f,g}^i$ is called the value vector of agent i .

The objective of agent i is to choose the strategy that maximizes its expected return $\mathbf{v}_{f,g}^i$. Agents are assumed to be noncooperative and choose strategies independently. We also assume that the strategies chosen by agents are stationary, meaning that (\mathbf{f}, \mathbf{g}) is independent of time and history. In this context, an NE stationary strategies $(\mathbf{f}^*, \mathbf{g}^*)$ of the discounted stochastic game Γ_β is the one that componentwise satisfies

$$\mathbf{v}^1(\mathbf{f}^*, \mathbf{g}^*) \geq \mathbf{v}^1(\mathbf{f}, \mathbf{g}^*), \quad \forall \mathbf{f} \in F_S, \quad (5.3)$$

$$\mathbf{v}^2(\mathbf{f}^*, \mathbf{g}^*) \geq \mathbf{v}^2(\mathbf{f}^*, \mathbf{g}), \quad \forall \mathbf{g} \in G_S, \quad (5.4)$$

where F_S is the strategy set of agent 1 and G_S is the strategy set of agent 2. The NE concept implies that neither agent has the incentive to unilaterally deviate from the equilibrium point $(\mathbf{f}^*, \mathbf{g}^*)$ to gain a higher reward.

5.3.2 Game Structures

In our model, the state space can be partitioned based on the controller of the state, as illustrated in Figure 5.1. When the healthcare setting is Hm , agent PA is the controller; when the healthcare setting is Po , agent PCP becomes the controller; when the healthcare setting is Hs , the game becomes a Markov process without agents' control. Mathematically,

we introduce the following formal definition.

Definition 1. *A switching-control stochastic game (SCSG) is a game for which the state space S can be partitioned into disjoint subsets such that [143]*

$$p(s'|s, a_i^1, a_1^2) = p(s'|s, a_i^1, a_2^2), \quad \forall s \in S^1, a_i^1, a_1^2, a_2^2, \quad (5.5)$$

$$p(s'|s, a_1^1, a_j^2) = p(s'|s, a_2^1, a_j^2), \quad \forall s \in S^2, a_1^1, a_2^1, a_j^2. \quad (5.6)$$

Define the following disjoint subsets of the state space S in our model:

$$s = (h, l, Hm) \in S^{PA}, \quad \forall h, l,$$

$$s = (h, l, Po) \in S^{PCP}, \quad \forall h, l,$$

$$s = (h, l, Hs) \in S^\phi, \quad \forall h, l.$$

Our stochastic game has the following structure:

$$p(s'|s, a_i^{PA}, a_1^{PCP}) = p(s'|s, a_i^{PA}, a_2^{PCP}), \quad \forall s \in S^{PA}, a_i^{PA}, a_1^{PCP}, a_2^{PCP}, \quad (5.7)$$

$$p(s'|s, a_1^{PA}, a_j^{PCP}) = p(s'|s, a_2^{PA}, a_j^{PCP}), \quad \forall s \in S^{PCP}, a_1^{PA}, a_2^{PA}, a_j^{PCP}. \quad (5.8)$$

Since in the state $s \in S^\phi$, both agents are inactive, the property in Definition 1 is not violated. Our model falls into the special class of SCSGs, where two agents take turns to control the probabilistic transition of the game. This property reflects the realistic healthcare setting, and can also be leveraged to facilitate the search for NEs of the theoretical model. Next, we introduce the following formal definition.

Definition 2. *A stochastic game is said to be a game of perfect information if the state space S can be partitioned into two disjoint subsets S^1 and S^2 such that $|A_s^2| = 1$, for $s \in S^1$ and $|A_s^1| = 1$, for $s \in S^2$. [30]*

According to Definition 2, a game of perfect information is a special class of SCSGs. The structural properties imply that in the states controlled by agent 1, agent 2 is inactive since it

only has one action available. The probabilistic transitions and the reward functions depend only on the current state and agent 1's action, and are independent of agent 2's action. Similarly, in the states controlled by agent 2, agent 1 is inactive and does not affect the probabilistic transitions or the reward functions. Hence, it is evident that our model is not only a SCSG, but also with perfect information.

5.3.3 Solutions

Extensive research has been done on proving the existence of certain types of NEs in SGs with special structures and on finding solution algorithms [143, 144, 145, 99, 146]. On the class of SCSGs and games with perfect information, the following findings have been proved by prior studies.

Lemma 3. *For a stochastic game with perfect information, both agents possess uniform discount optimal pure stationary strategies. [30]*

A proof of Lemma 3 can be found in the paper by Thuijsman and Raghavan [146]. Lemma 3 implies that in searching for the NEs of our model, we only need to focus our attention to pure strategies. Mathematically, there exists a strategy pair $(\mathbf{f}^*, \mathbf{g}^*)$, such that

$$\begin{aligned}
v^1(\mathbf{f}^*, \mathbf{g}^*) &\geq v^1(\mathbf{f}, \mathbf{g}^*), \quad \forall \mathbf{f} \in F_S, \\
v^2(\mathbf{f}^*, \mathbf{g}^*) &\geq v^2(\mathbf{f}^*, \mathbf{g}), \quad \forall \mathbf{g} \in G_S, \\
\sum_{i=1}^{M(s)} f^*(s, a_i^{PA}) &= 1, \quad \forall s, \\
f^*(s, a_i^{PA}) &= 0 \text{ or } 1, \quad \forall s, i, \\
\sum_{j=1}^{M(s)} g^*(s, a_j^{PCP}) &= 1, \quad \forall s, \\
g^*(s, a_j^{PCP}) &= 0 \text{ or } 1, \quad \forall s, j.
\end{aligned}$$

For all SCSGs, including the games with perfect information, the orderfield property has been proved to hold, and one can expect to develop finite algorithms for finding a solution

[144]. Based on the general-sum, infinite-horizon, discounted characteristics of our game, we use the nonlinear programming approach proposed by Filar and Vrieze [30] to find the NE solutions. Denote the following program as NLP-1.

NLP-1:

$$\begin{aligned} & \min \left\{ \sum_{i=1}^2 \mathbf{1}^T [\mathbf{v}^i - \mathbf{r}^i(\mathbf{f}, \mathbf{g}) - \beta P(\mathbf{f}, \mathbf{g}) \mathbf{v}^i] \right\} & (5.9) \\ \text{s.t. } & R^1(s)\mathbf{g}(s) + \beta T(s, \mathbf{v}^1)\mathbf{g}(s) \leq v^1(s) \mathbf{1}_{M^1(s)}, \quad s \in S, \\ & \mathbf{f}(s)R^2(s) + \beta \mathbf{f}(s)T(s, \mathbf{v}^2) \leq v^2(s) \mathbf{1}_{M^2(s)}^T, \quad s \in S, \\ & (\mathbf{f}, \mathbf{g}) \in \mathbf{F}_S \times \mathbf{G}_S, \end{aligned}$$

where $i=1,2$ refers to agent 1 or 2, $R^i(s) = [r^i(s, a_i^1, a_j^2)]_{a_i^1=1, a_j^2=1}^{M^1(s), M^2(s)}$ is the i^{th} agent's immediate reward matrix in state s , and the matrices

$$T(s, \mathbf{v}) = \left[\sum_{s' \in S} p(s'|s, a_i^1, a_j^2) v(s') \right]_{a_i^1=1, a_j^2=1}^{M^1(s), M^2(s)}.$$

The two sets of constraints in NLP-1 include $2 \times N$ inequalities and represent the optimality conditions required for searching for the global minimum to the program.

Additionally, let $\mathbf{z}^T = [(\mathbf{v}^1)^T, (\mathbf{v}^2)^T, \mathbf{f}, \mathbf{g}^T]$ be a $(2N + M^1 + M^2)$ -dimensional vector of variables. Denote the objective function of NLP-1 as $\psi(\mathbf{z})$. We have the following lemma.

Lemma 4. *Consider a point $\hat{\mathbf{z}}^T = [(\hat{\mathbf{v}}^1)^T, (\hat{\mathbf{v}}^2)^T, \hat{\mathbf{f}}, \hat{\mathbf{g}}^T]$. Then the strategy part $[(\hat{\mathbf{f}}, \hat{\mathbf{g}}^T)]$ of $\hat{\mathbf{z}}^T$ forms a NE point of the general-sum discounted game Γ_β if and only if $\hat{\mathbf{z}}$ is the global minimum of NLP-1 with $\psi(\hat{\mathbf{z}}) = 0$. [30]*

The proof of Lemma 4 can be found in Filar and Vrieze [30]. Lemma 4 implies that searching for NE solutions is equivalent to searching for the global minimum to NLP-1. Based upon NLP-1 and Lemma 4, we further leverage the properties given by SCSGs and games with perfect information and formulate a modified nonlinear program, denoted by NLP-2, to solve our model.

NLP-2:

$$\min \{ \mathbf{1}^T [\mathbf{v}^{PA} + \mathbf{v}^{PCP} - \mathbf{r}^{PA}(\mathbf{f}, \mathbf{g}) - \mathbf{r}^{PCP}(\mathbf{f}, \mathbf{g}) - \beta P(\mathbf{f}, \mathbf{g}) \mathbf{v}^{PA} - \beta P(\mathbf{f}, \mathbf{g}) \mathbf{v}^{PCP}] \} \quad (5.10)$$

$$s.t. \quad R^{PA}(s)\mathbf{g}(s) + \beta T(s, \mathbf{v}^{PA})\mathbf{g}(s) \leq v^{PA}(s) \mathbf{1}_{M^{PA}(s)}, \quad s \in S,$$

$$\mathbf{f}(s)R^{PCP}(s) + \beta \mathbf{f}(s)T(s, \mathbf{v}^{PCP}) \leq v^{PCP}(s) \mathbf{1}_{M^{PCP}(s)}^T, \quad s \in S,$$

$$\sum_{i=1}^{M^{PA}(s)} f(s, a_i^{PA}) = 1, \quad s \in S,$$

$$f(s, a_i^{PA}) = 0 \text{ or } 1, \quad \forall i, \quad s \in S,$$

$$\sum_{j=1}^{M^{PCP}(s)} f(s, a_j^{PCP}) = 1, \quad s \in S,$$

$$g(s, a_j^{PCP}) = 0 \text{ or } 1, \quad \forall j, \quad s \in S,$$

$$g[(h, l, Po), \tilde{a}_j^{PCP}] = g[(h, l', Po), \tilde{a}_j^{PCP}], \quad j = 1, 2, \quad \forall h, l, l', \quad \tilde{a}_j^{PCP} \in A_{(h, l, Po)}^{PCP},$$

$$(\mathbf{f}, \mathbf{g}) \in \mathbf{F}_S \times \mathbf{G}_S.$$

In NLP-2, constraints (3)-(6) limit the feasible region to pure strategies only. Due to the existence of pure NE strategies (given by Lemma 1), these constraints do not affect the optimality of NLP-2 but can reduce the computational efforts of solving the program significantly. Constraint (7) implies the assumption that when agent PCP chooses between high effort or low effort in the healthcare setting Po , it can only observe health status. In other words, agent PCP cannot distinguish patient's lifestyle before choosing an effort level first. The introduction of this constraint may affect the global minimum of NLP-2. In certain cases, the global minimum to NLP-2 is still an NE solution, namely, $\psi(\hat{\mathbf{z}}) = 0$. We call these solutions the *first best solution*. In other cases, the global minimum is not an NE, namely $\psi(\hat{\mathbf{z}}) > 0$. That is, the NE solutions of the game do not satisfy constraint (7). We call these global optima the *second best solution*. In the following case study, we identify the first best solution and consider the second best solution as the optimal strategy pair when the first best solution does not exist.

5.4 Case Study

5.4.1 A Coronary Heart Disease (CHD) Example

CHD is the leading cause of death for both men and women. It is also the diagnostic group with the highest health care costs, estimated to cost \$108.9 billion each year [147]. The risk factors of someone getting CHD may be characterised as non-modifiable or modifiable [148]. The non-modifiable risk factors include age, gender, ethnic origin, family disease history, etc. The modifiable risk factors are physiological or behavioral, mainly referring to a person's lifestyle choices. Some leading risk determinants for CHD, such as high blood pressure and high cholesterol, are heavily influenced by lifestyle choices related to poor diet, physical inactivity, alcohol and nicotine use [149]. The prevention and treatment of CHD encompasses many areas of clinical medicine and public health [150]. In this case study, we limit our attention on patient's primary care engagement decision, lifestyle choices, i.e., the modifiable risk factors, and physician's effort level during clinical encounters.

5.4.1.1 Patient State

To define patient health status, we consider two prevalent CHD classification system. The American College of Cardiology (ACC) and American Heart Association (AHA) classify chronic heart failure into four stages [151]:

- Stage A: High risks for developing HF in the future but no functional or structural heart disorder;
- Stage B: Structural heart disorder but no symptoms at any stage;
- Stage C: Previous or current symptoms of heart failure in the context of an underlying structural heart problem, but managed with medical treatment;

- Stage D: Advanced disease requiring hospital-based support, a heart transplant or palliative care.

According to the New York Heart Association (NYHA) functional classification, CHD has four classes [152]:

- Class I: No limitation is experienced in any activities; there are no symptoms from ordinary activities;
- Class II: Slight, mild limitation of activity; the patient is comfortable at rest or with mild exertion;
- Class III: Marked limitation of any activity; the patient is comfortable only at rest;
- Class IV: Any physical activity brings on discomfort and symptoms occur at rest.

Comparing with the NYHA system, the ACC-AHA system covers broader CHD disease progression stages and includes some early stages of CHD, where proactive prevention and proper management are particularly important [153]. Hence in this case study, we adopt the ACC-AHA system and define patient health status as $h = \{1, 2, 3, 4\}$, referring to Stage A, B, C, D in the classification system respectively. Based on the nature of the stages, we define $h = 1, 2, 3$ as chronic conditions and $h = 4$ as an acute episode. Current lifestyle l and healthcare setting k remain the same as defined previously.

5.4.1.2 Actions

Both agents' actions are the same as defined in Section 5.2.3.

5.4.1.3 State Transition Probabilities

The TPMs for movement between ACC-AHA stages are estimated from the published literature detailing the long-term monthly health state transitions of CHD patients receiving

medical therapy alone [154]. The published data was originally estimated using the NYHA system. Due to limited data, we use the mapping method proposed by ACC and AHA [152, 153] (details in Appendix B.3), and translate the literature data into the TPMs based on the ACC-AHA system.

Recall in Section 5.2.4, \mathcal{H}_{Po} is the health status TPM under the influence of primary care and \mathcal{H}_{Hs} is the health status TPM under the influence of acute care. In this case study, we have

$$\mathcal{H}_{Po} = \begin{array}{c} 1 \\ 2 \\ 3 \end{array} \begin{array}{cccc} 1 & 2 & 3 & 4 \\ \left(\begin{array}{cccc} 0.95 & 0.05 & 0.00 & 0.00 \\ 0.04 & 0.76 & 0.19 & 0.01 \\ 0.00 & 0.04 & 0.95 & 0.01 \end{array} \right),$$

$$\mathcal{H}_{Hs} = \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \end{array} \begin{array}{cccc} 1 & 2 & 3 & 4 \\ \left(\begin{array}{cccc} 0.00 & 0.00 & 0.21 & 0.79 \end{array} \right).$$

Recall that \mathcal{H}_B is the health status TPM under the influence of lifestyle B at home, and \mathcal{H}_{Nb} is the health status TPM under the influence of lifestyle Nb at home. We use \mathcal{H}_{Po} as our baseline values and derive the values for \mathcal{H}_B and \mathcal{H}_{Nb} with assumptions documented in Appendix B.4. We have

$$\mathcal{H}_B = \begin{array}{c} 1 \\ 2 \\ 3 \end{array} \begin{array}{cccc} 1 & 2 & 3 & 4 \\ \left(\begin{array}{cccc} 0.93 & 0.07 & 0.00 & 0.00 \\ 0.04 & 0.72 & 0.23 & 0.01 \\ 0.00 & 0.04 & 0.86 & 0.10 \end{array} \right),$$

$$\mathcal{H}_{Nb} = \begin{array}{c} 1 \\ 2 \\ 3 \end{array} \begin{array}{cccc} 1 & 2 & 3 & 4 \\ \left(\begin{array}{cccc} 0.90 & 0.10 & 0.00 & 0.00 \\ 0.04 & 0.68 & 0.27 & 0.01 \\ 0.00 & 0.03 & 0.81 & 0.16 \end{array} \right).$$

5.4.1.4 Rewards

Both agents' rewards are the same as defined in Section 5.2.3. Specifically, health utility values $u^{PA}(h)$ are based on three published literature with detailed estimation of patient health utilities [154, 155, 156] (details in Appendix B.4). Again, we translate the literature data into our model input based on the ACC-AHA system. We have

$$u^{PA}(1) = 1.00, u^{PA}(2) = 0.85, u^{PA}(3) = 0.71, u^{PA}(4) = 0.43.$$

5.4.1.5 Other Parameters

Additionally, we assume the following parameter values: if the current lifestyle is Nb , a high effort of agent PCP will lead to lifestyle B in the next period with a probability $p_{h,B} = 0.9$; and if a low effort decision is chosen, the probability of lifestyle Nb in the next period is $p_{l,Nb} = 0.9$. We also assume that the discount factor is $\beta = 0.99$.

Next, we use the aforementioned model input to perform the numerical analysis. For all calculations of NEs and/or optimal strategies, NLP-2 is implemented and solved in Mathematica®. We conduct the analysis by focusing on the influence of incentives on patient and physician respectively.

5.4.2 Analysis: Patient Incentives

Agent PA makes two types of decisions: (1) whether to go to primary care, and (2) which lifestyle to adopt. By examining the TPMs and the reward functions, we identify the key variables that influence agent PA's decisions listed in Table 5.1: patient's primary care payment, hospitalization payment, patient's action cost, and agent PCP's decisions. The variables m_1^{PA} , m_2^{PA} , c_1^{PA} , c_2^{PA} are varied within certain ranges with an incremental step of 0.01. We further make the assumption based on reality that the action cost of maintaining lifestyle B is always lower than switching to lifestyle B . Hence, the value ranges of these

Table 5.1: Key variables for patient incentives analysis

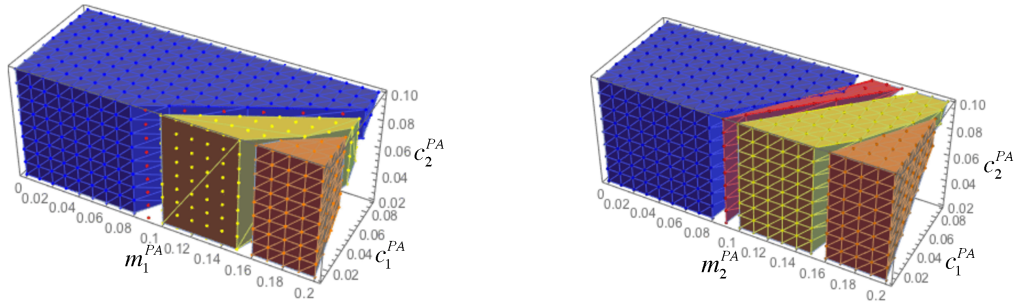
Parameter	Notation	Value Range
Primary care payment - High effort	m_1^{PA}	[0.00, 0.20]
Primary care payment - Low effort	m_2^{PA}	[0.00, 0.20]
Action cost - Maintaining a beneficial lifestyle	c_1^{PA}	[0.01,0.10)
Action cost - Switching to a beneficial lifestyle	c_2^{PA}	(0.01,0.10]
Hospitalization payment	m_{Hs}^{PA}	0.2
Physician's action	$A_{(h,l,Po)}^{PCP}$	Either <i>high</i> for the entire set or <i>low</i> for the entire set

two variables are slightly different. We can also fix one of the variables in agent PA's reward functions at a constant value, while varying the values of other variables. Without loss of generality, we choose hospitalization payment m_{Hs}^{PA} and fix its value at 0.2. Additionally, to analyze the influence of physician's decision, we consider the NEs where agent PCP chooses either high effort or low effort for all patient states.

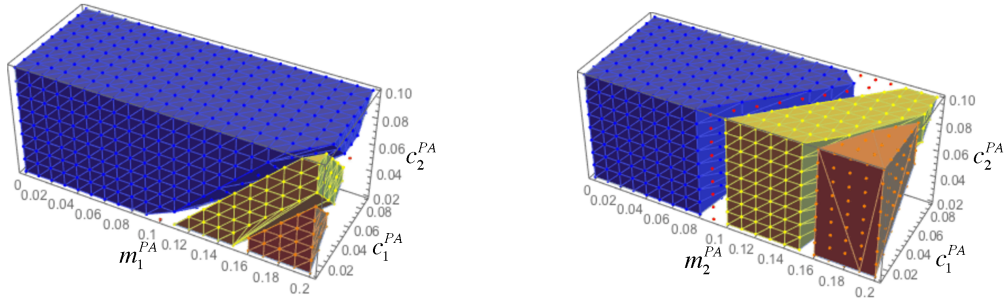
For each numerical case, NLP-2 is solved to obtain the optimal solution(s). In any optimal solution, the objective function Eq. 5.10 has a value of 0. Figure 5.2 gives an overview of the numerical results of the patient incentives analysis. Each graph includes a total of 945 numerical cases. Every dot in the graph represents an NE solution to the game.

Figure 5.2a showcases how a patient chooses to have a primary care visit given a group of key variables. We use colored dots to represent the count of primary care visit in the three chronic conditions, i.e., $h = 1, 2, 3$. For example, a blue dot represents the case that the patient chooses primary care visit in all three chronic conditions; a red dot represents that the patient chooses primary care in two of the three status; a yellow dot means that the patient only visits primary care in one of the three status; and an orange dot means that the patient always chooses to stay at home and never use primary care. Figure 5.2b showcases how a patient chooses her future lifestyle given the same group of variables. Similarly, we use colored dots to represent the number of choosing lifestyle B in the three chronic conditions.

(a) Primary care visit for a patient with *B* lifestyle, high effort (b) Primary care visit for a patient with *B* lifestyle, low effort



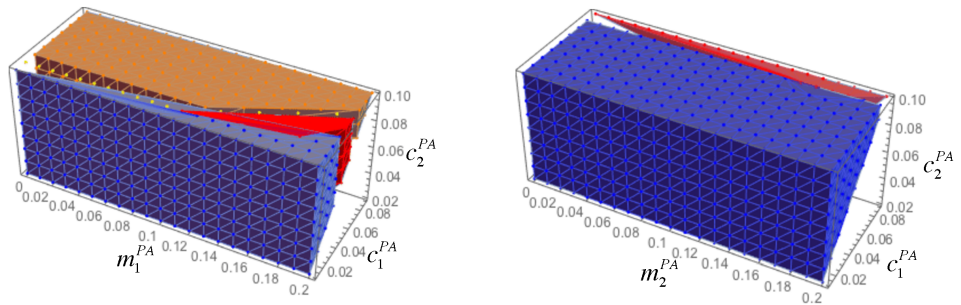
(c) Primary care visit for a patient with *NB* lifestyle, high effort (d) Primary care visit for a patient with *NB* lifestyle, low effort



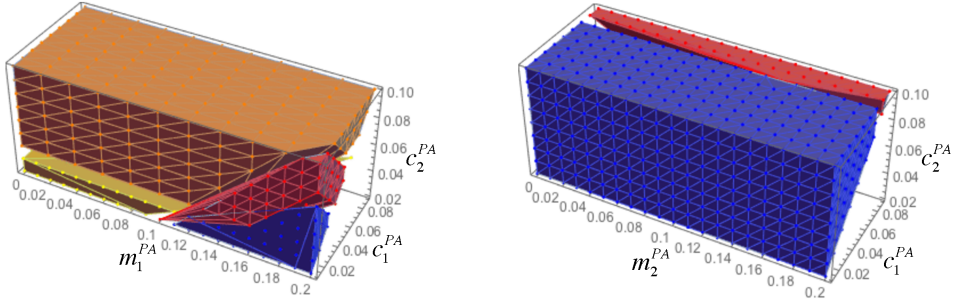
■ always PCP ■ sometimes PCP ■ occasionally PCP ■ never PCP

(a) Primary care visit

(a) Lifestyle choices for a patient with *B* lifestyle, high effort (b) Lifestyle choices for a patient with *B* lifestyle, low effort



(c) Lifestyle choices for a patient with *NB* lifestyle, high effort (d) Lifestyle choices for a patient with *NB* lifestyle, low effort



■ always B ■ sometimes B ■ occasionally B ■ never B

(b) Lifestyle choices

Figure 5.2: Numerical results of the patient incentives analysis

Table 5.2: Physician's influence on patient's primary care visit

Primary care visit	Always (Blue)	2 out of 3 (Red)	1 out of 3 (Yellow)	Never (Orange)
lifestyle B , high effort	67.4%	4.1%	18.2%	10.3%
lifestyle B , low effort	55.1%	5.2%	25.6%	14.1%
lifestyle Nb , high effort	86.6%	0.3%	9.6%	3.5%
lifestyle Nb , low effort	55.3%	5.0%	25.9%	13.8%

A blue dot represents the case that the patient always chooses lifestyle B for the next time period; a red dot represents that the patient chooses lifestyle B in two of the three chronic conditions; a yellow dot means that the patient only chooses lifestyle B in one of the three conditions; and an orange dot means that the patient always chooses lifestyle Nb for the next time period. We further draw one convex hull for each color in Mathematica® to display these different dot regions.

Next, we decompose patient's incentive drivers and analyze their influences individually.

Patient Incentive 1. *Physician's high effort encourages patient's engagement in primary care.*

When comparing (a1) with (a2) and (a3) with (a4) in Figure 5.2a, we see that the blue convex hull is larger when high effort is chosen, whereas the red, yellow, and orange convex hulls are generally larger when low effort is chosen. Table 5.2 illustrates such differences with respect to physician's effort level in details. Among all the 945 cases tested, physician's high effort motivates the patient of lifestyle B to spend a primary care visit in 67.4% cases, while for low effort, the percentage is only 55.1%. Similarly, for a patient with lifestyle Nb , 13.8% of the total cases never use primary care when low effort is given, whereas the percentage reduces significantly to 3.5% when high effort is given. The results illustrate that with more effort from the physician during a clinical encounter, the patient is more likely to engage in primary care.

Patient Incentive 2. *High primary care payment discourages patient's engagement in pri-*

mary care.

In Figure 5.2a, as the primary care payment m_1^{PA} or m_2^{PA} (x axis) increases, the NE solution changes from “always” visiting primary care (blue), to “sometimes” or “occasionally” (red or yellow), and then to “never” (orange). For instance, in Figure 5.2(a1), when $c_1^{PA} = 0.01$, $c_2^{PA} = 0.02$, the patient always visits primary care if $m_1^{PA} < 0.09$; the patient sometimes visits primary care if $0.09 \leq m_1^{PA} \leq 0.15$; and the patient never visit primary care if $m_1^{PA} > 0.15$. In Figure 5.2(a3), when $c_1^{PA} = 0.02$, $c_2^{PA} = 0.05$, the patient always visits primary care if $m_1^{PA} < 0.15$; the patient sometimes visits primary care if $0.15 \leq m_1^{PA} \leq 0.18$; and the patient never visit primary care if $m_1^{PA} > 0.18$. While the transition points of NEs depends on parameters including c_1^{PA} , c_2^{PA} , and $A_{(h,l,Po)}^{PCP}$; the transition trajectory is the same among all numerical cases. That is, as primary care payment increases, the patient is discouraged from using primary care and will stay at home more frequently.

Patient Incentive 3. *Low maintaining cost and low switching cost can discourage patient’s engagement in primary care.*

To examine the influences of action cost c_1^{PA} and c_2^{PA} , we take the cross sections of the convex hulls in Figure 5.2a and mark all the NEs using the same color code. Among all the cross sections, three typical patterns can be identified (Figure 5.3). Pattern 1 is from Figure 5.2(a1) and $m_1^{PA} = 0.05$. In all the NEs displayed, the patient always chooses primary care visit; hence action costs do not affect patient’s decision in this pattern. Pattern 2 is from Figure 5.2(a1) and $m_1^{PA} = 0.20$. Three types of NEs are included in this pattern. As maintaining cost increases, the patient uses primary care more frequently; on the other hand, an increasing switching cost does not affect patient’s decision. Pattern 3 is from Figure 5.2(a3) and $m_1^{PA} = 0.20$. All four types of NEs are included in this pattern, and maintaining cost and switching cost both increase the frequency of primary care visit. The numerical results indicate that while in some cases, action costs do not affect patient’s decisions, in other cases, low maintaining cost and/or low switching cost can incentivize patient to stay at home and self-manage health, instead of having primary care.

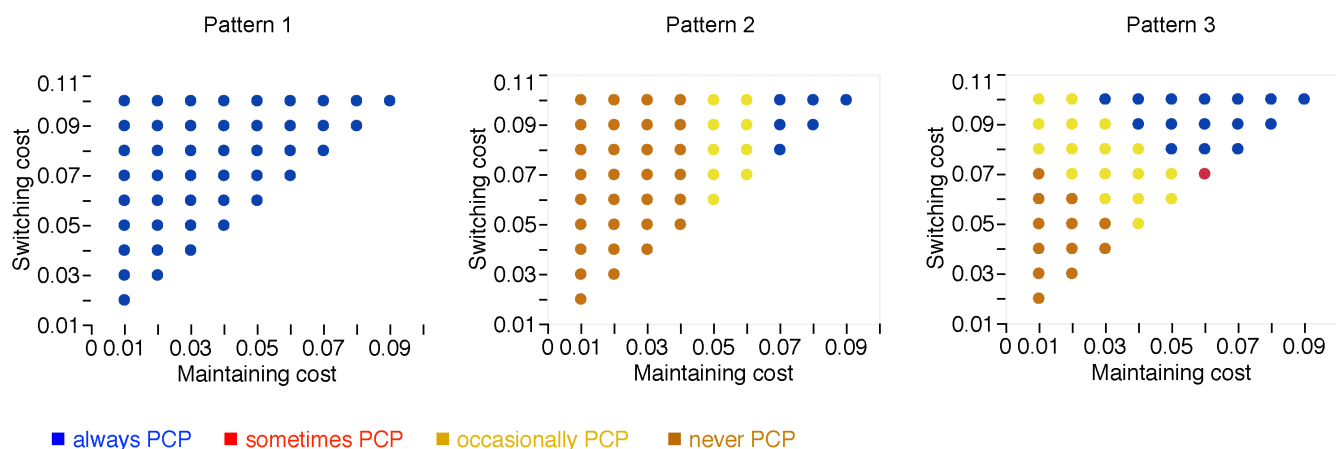


Figure 5.3: Action costs' influence on primary care visit

Patient Incentive 4. *Physician's high effort triggers the patient to adopt beneficial lifestyle after clinical encounter, but allows patients to slack on healthy lifestyle effort in the long run.*

When agent PCP chooses a high level of effort, it can motivate the patient to switch from non-beneficial lifestyle to beneficial lifestyle after the clinical encounter, illustrating the cue to action influence. Nevertheless, this influence may also have countereffect such that the patient may slack on maintaining a healthy lifestyle in the long run. When comparing (b1) with (b2) and (b3) with (b4) in Figure 5.2b, we see that the blue convex hull is larger when low effort is chosen, whereas the red, yellow, and orange convex hulls are larger when high effort is chosen. Note that Figure 5.2b shows agent PA's equilibrium decision before the clinical encounter, since agent PA only makes decision when the healthcare setting is Hm . We further use Table 5.3 to illustrate lifestyle decision differences with respect to physician's effort level in details. For a patient with lifestyle B , in 96.1% cases, she will maintain lifestyle B if agent PCP chooses low effort in the future clinical encounter. On the contrary, the patient will continue with lifestyle B in only 29.7% cases, if agent PCP chooses high effort in the future clinical encounter. For a patient with lifestyle Nb , she is even more disincentivized to proactively manage health, as the percentage of blue is only 4.4% in high effort scenario; whereas in low effort scenario, the percentage is 93.4%, which is significantly higher.

Table 5.3: Physician's influence on lifestyle choice

Beneficial lifestyle	Always (Blue)	2 out of 3 (Red)	1 out of 3 (Yellow)	Never (Orange)
Current lifestyle B , high effort	29.7%	9.1%	11.6%	49.6%
Current lifestyle B , low effort	96.1%	3.9%	0%	0%
Current lifestyle Nb , high effort	4.4%	8.8%	3.7%	83.1%
Current lifestyle Nb , low effort	93.4%	6.6%	0%	0%

Patient Incentive 5. *Low maintaining cost and low switching cost incentivize patients to self-manage health.*

Again, the cross sections of each convex hull in Figure 5.2b are used to examine the influences of action cost on lifestyle choices. Assume a primary care payment cost of 0.20, we have the four patterns in Figure 5.4. In all four patterns, we see that as maintaining cost and/or switching cost decreases, the patient is more likely to maintain or switch to lifestyle B in the next time period. This is intuitive, since a lower action cost reduces the perceived barrier that affects patient's health-promoting behavior.

5.4.3 Analysis: Physician Incentives

Agent PCP decides the effort level in every clinical encounter. The key variables that influence agent PCP's decision listed in Table 5.4 are: physician's primary care reimbursement, health disutility due to hospitalization, and agent PA's decisions. The variables n_1^{PCP} and n_2^{PCP} are varied within certain ranges with an incremental step of 0.01. The variable u_{Hs}^{PCP} is fixed at a value of 0.1, 0.2, or 0.3. We further pick three key strategies that a patient plays frequently in NEs and also in practices. The three strategies are

- **PA strategy 1**

$$f[(h, B, Hm), (maintain, PCP)] = 1,$$

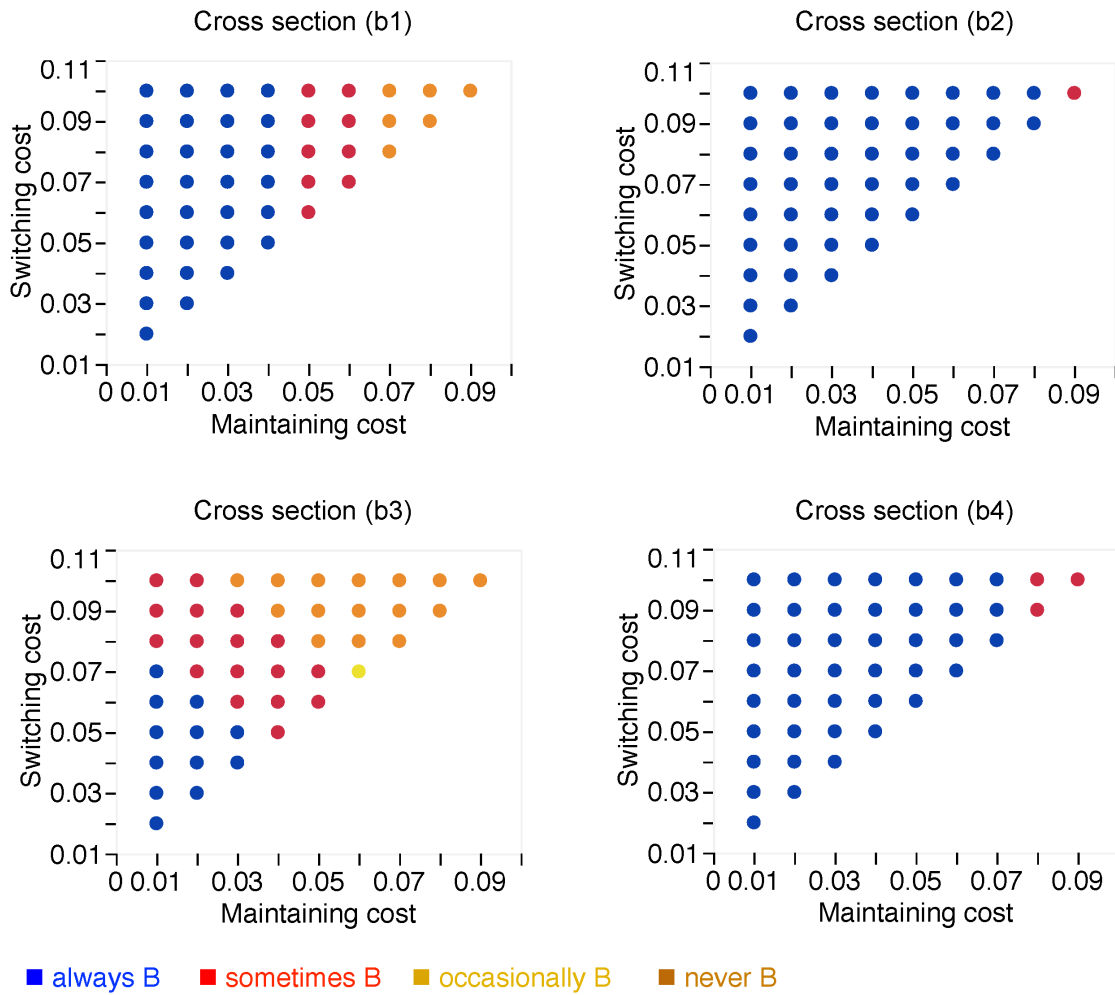


Figure 5.4: Action costs' influence on lifestyle choice

Table 5.4: Key variables for physician incentives analysis

Parameter	Notation	Value Range
Primary care reimbursement - High effort	n_1^{PCP}	[0.00, 0.20]
Primary care reimbursement - Low effort	n_2^{PCP}	[0.00, 0.20]
Health disutility	$u_{H_s}^{PCP}$	0.1, 0.2 or 0.3
Patient's action	$A_{(h,B,Hm)}^{PA}$	Three key strategies

$$f[(h, Nb, Hm), (status\ quo, PCP)] = 1;$$

- **PA strategy 2**

$$f[(1, B, Hm), (maintain, home)] = 1,$$

$$f[(2, B, Hm), (maintain, PCP)] = f[(3, B, Hm), (maintain, PCP)] = 1,$$

$$f[(1, Nb, Hm), (status\ quo, home)] = 1,$$

$$f[(2, Nb, Hm), (status\ quo, PCP)] = f[(3, Nb, Hm), (status\ quo, PCP)] = 1;$$

- **PA strategy 3**

$$f[(1, B, Hm), (maintain, home)] = f[(2, B, Hm), (maintain, home)] = 1,$$

$$f[(3, B, Hm), (maintain, PCP)] = 1,$$

$$f[(1, Nb, Hm), (status\ quo, home)] = f[(2, Nb, Hm), (status\ quo, home)] = 1,$$

$$f[(3, Nb, Hm), (status\ quo, PCP)] = 1.$$

Again, for each numerical case, NLP-2 is solved to obtain the optimal solution(s). Figure 5.5 gives an overview of the numerical results of the physician incentives analysis. Each row represents agent PCP's best response to the given PA strategy. Each column represents a level of health disutility. In each graph, a total of 441 cases were tested. Every dot represents an optimal strategy to the game. Note that agent PCP's strategy includes one action for each health status, namely, $a_{(1,l,Po)}^{PCP}$, $a_{(2,l,Po)}^{PCP}$, and $a_{(3,l,Po)}^{PCP}$, with the action set $A_{(h,l,Po)}^{PCP} = \{high, low\}$. In Figure 5.5, we identify four different PCP strategies:

- **PCP strategy 1:** $g[(1, l, Po), high] = 1$, $g[(2, l, Po), high] = 1$, $g[(3, l, Po), high] = 1$;
color coded in blue;
- **PCP strategy 2:** $g[(1, l, Po), low] = 1$, $g[(2, l, Po), high] = 1$, $g[(3, l, Po), high] = 1$;
color coded in red;
- **PCP strategy 3:** $g[(1, l, Po), low] = 1$, $g[(2, l, Po), low] = 1$, $g[(3, l, Po), high] = 1$;
color coded in yellow;
- **PCP strategy 4:** $g[(1, l, Po), low] = 1$, $g[(2, l, Po), low] = 1$, $g[(3, l, Po), low] = 1$;
color coded in orange.

Next, we decompose physician's incentive drivers and analyze their influences individually.

Physician Incentive 1. *The difference between high effort reimbursement and low effort reimbursement is the dominant influencer for physician's effort level.*

The transition lines of NE strategies in Figure 5.5 lie closely to the 45-degree line of "high effort reimbursement=low effort reimbursement". When high effort reimbursement is higher than low effort reimbursement, agent PCP is more likely to choose high effort level to gain a better payoff. Below the 45-degree line, agent PCP often prefers low effort, since this action gives a better payoff. Thus, it is evident that the monetary incentives have direct effect on agent PCP's decision.

Physician Incentive 2. *A higher disutility of adverse health outcomes widens the transition region of physician's strategy.*

While the different regions of optimal strategies are highly dependent on financial reimbursement, the transition regions of optimal strategies are sensitive to physician's disutility resulting from adverse health outcomes. For example, for PA strategy 2, when $n_1^{PCP} = 0$, $n_2^{PCP} = 0.02$, $u_{H_s}^{PCP} = 0.1$, agent PCP's optimal strategy is to choose low effort for all patients. When $u_{H_s}^{PCP} = 0.2$, the optimal strategy is to choose high effort only for the patient

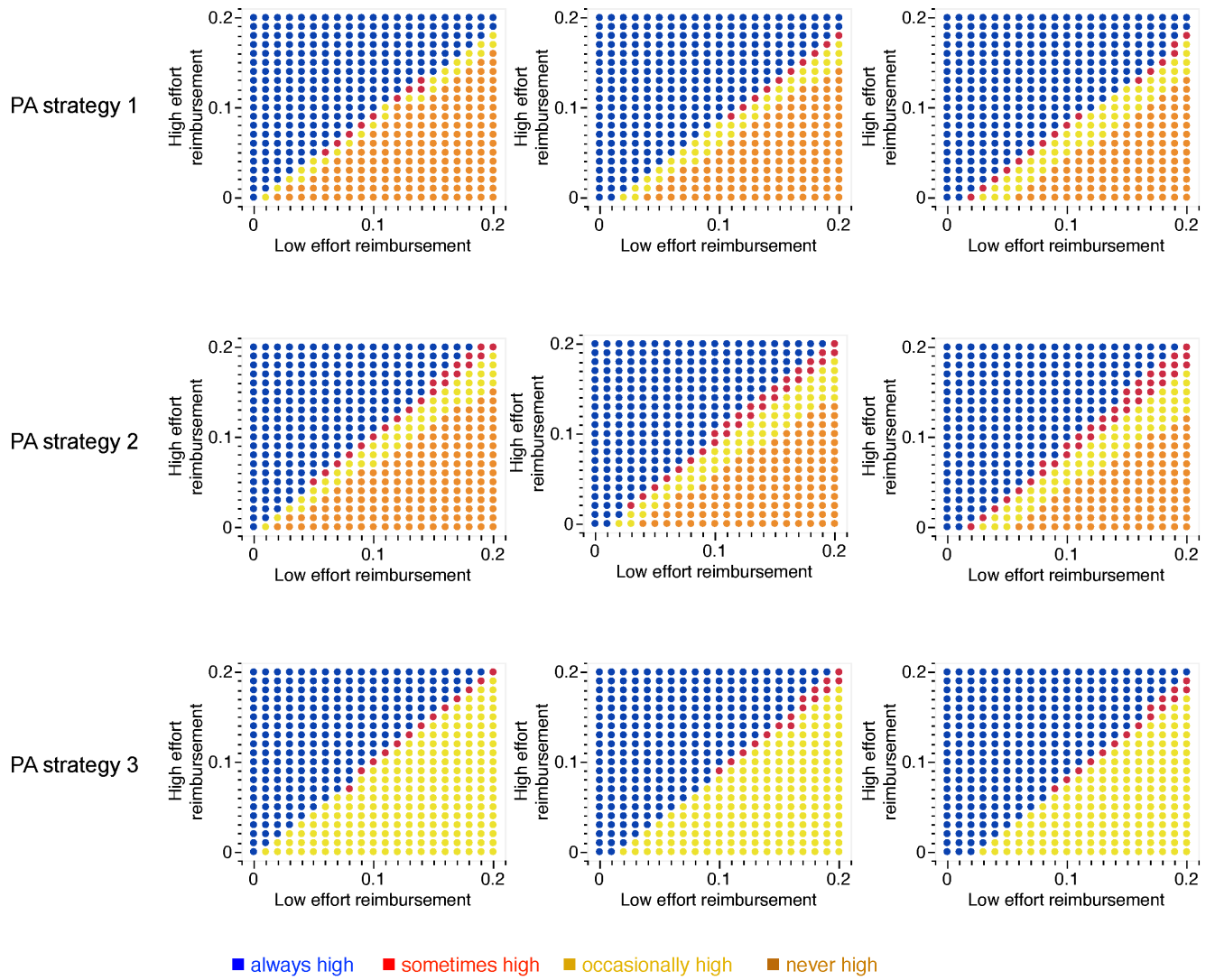


Figure 5.5: Numerical results of the physician incentives analysis

with $h = 3$. When $u_{Hs}^{PCP} = 0.3$, the optimal strategy is to choose high effort for the patient with $h = 2$ or 3 . As the disutility u_{Hs}^{PCP} increases, agent PCP puts more weight on the health outcome of a patient and less weight on the reimbursement component, and is willing to spend more effort during a clinical encounter beyond the consideration of monetary incentives.

Physician Incentive 3. *Patient's primary care visit frequency influences physician's choice of effort level.*

For PA strategy 1, agent PA always visits a PCP; for PA strategy 2, agent PA visits a PCP when health status is $h = 2$ or 3 ; while for PA strategy 3, agent PA only visits a PCP when health status is $h = 3$. By comparing the three rows in Figure 5.5, we find that for PA strategy 2, agent PCP is more likely to use strategy 2, e.g., high effort for the patient with $h = 2$ or 3 , than the other two rows. For PA strategy 3, agent PCP tends to use more strategy 3, e.g., high effort for the patient with $h = 3$, than the other two rows. Hence, agent PCP's choice of effort level is highly dependent on patient's primary care visit patterns.

5.5 Conclusions

In this chapter, we discuss a practical and important health care problem: chronic disease management. The research objective is identifying and designing healthcare incentives that lead to better chronic disease management. The decision processes of two major decision makers, patient and physician, are modeled as a two-level, multi-period stochastic game. The patient state is considered to be partially random and partially controlled by both decision makers. The health belief model is incorporated to capture the behavioral aspect of patients and physicians, accounting for their intrinsic and extrinsic, financial and non-financial motivations. Our model is formulated as a general-sum stochastic game with perfect information and switching control structure. Leveraging these structural properties, we use a nonlinear programming approach to find the Nash equilibria and/or the optimal strategies

of the game.

In the analysis part, we examine how incentives and interdependencies affect patients' engagement in health promoting activities and physicians' delivery of primary care services. The coronary heart disease is chosen as a case study example. Various literature data is used as the model input. We focus on the following incentive drivers: the effect of physician's decision on patient's decisions; the effect of patient's decisions on physician's decision; the effect of primary care payment and action cost on patient's decisions; the effect of reimbursement on physician's decision; and the effect of the disutility of adverse health outcomes on physician's decision. At the patient level, we find that proper incentives can enhance customers' purchasing behavior by reducing primary care costs and can promote customers' disease prevention activities by reducing action barriers. At the provider level, value- and outcome-based reimbursements can increase effort spent and promote care coordination between physicians and patients. Overall, a re-alignment of incentives can improve the effectiveness of chronic disease management.

To the best of our knowledge, this work is the first to show a formal application of a game-theoretic model in the chronic disease management context. Future work can be oriented towards the following directions. First, this model assumes that patients and physicians both have the perfect information about the patient health status; while in reality, the true health status of a patient may not be known with certainty. Observations, tests and procedures can provide probabilistic insights; hence, the competitive Markov decision processes used in our model can be improved to be partially observable Markov decision processes (POMDPs) in the future. Secondly, in terms of the structural properties, future work can discuss generalized model settings where switching-control and perfect information properties are in absence and more than two players are involved. Thirdly, our model involves the behavioral aspect of the agents, making it difficult to assign reward values such as health utilities. The estimation of transition probability matrices is also a challenge. In this work, we use data from published literature in the case study. Future work is needed to obtain quantitative estimates of model parameters through a combination of empirical and statistical approach.

Additionally, our model is limited to examine individual agents' discounted rewards. In future models, the long-term health outcomes, payments, and costs at societal level need to be accounted for and calculated. The cost-benefit and social welfare analysis can inform payers and policy makers of managerial insights and design better incentive mechanisms.

Chapter 6

Conclusions

This dissertation focuses on developing a multi-level decision-making model for the health care system, and on analyzing and improving multi-level incentive mechanisms in health care to the benefit of patients, physicians, hospitals, and payers. One of the challenges in health care incentive design has been the lack of effective models that can capture the complexities of multi-level systems and can provide decision support for stakeholders. In this dissertation, we developed a novel modeling approach based on multiscale decision theory (MSDT) that can account for the interdependencies between stakeholders across system levels, support decision processes, and enables the re-design of incentive programs. This chapter summarizes the work represented in the dissertation, highlights the key findings and identifies areas of future research.

6.1 Summary and Results

In the first part of the dissertation, we considered a system consisting of physicians, hospitals, and payers. We graphically captured the interactions among agents across system levels through an agent interdependence diagram and a detailed graphical representation. An

MSDT-based analytical approach was proposed that can evaluate the multi-level effects of incentives on the use and investment of medical technologies. MSSP ACOs were chosen as the problem setting, and CT as an exemplary medical technology. We analyzed the model as a sequential game. First, the payer decides how to reimburse and incentivize ACOs via MSSP by setting a cost benchmark. The ACO hospital then decides how the incentive is distributed between itself and the physicians. It also decides whether to make the CT scanner investment. At last, physicians decide the CT scan rate. The game was solved using the subgame perfect Nash equilibrium concept and the backward induction.

Through a numerical example, we found that incentives could alter the CT usage decision by physicians. However, a high cost benchmark can turn out to be ineffective in reducing the CT scan rate. In contrast, if the benchmark is too low, the cost target is unattainable and would result in penalty payment instead of rewards for ACOs. At the right benchmark level, the hospital will pass on all incentives to the physicians, which in turn lowers the CT scan rate. We also found that the CT scan rate is affected by the hospital's investment decision. A new and more advanced CT scanner will lead to more CT scans. Furthermore, a low benchmark will result in a CT scanner purchase, whereas a high benchmark will discourage an investment by the hospital.

In the second part of the dissertation, we extended the work of the previous chapter and formulated a MSDT model that captures the interactions and interdependencies among multiple health care agents, including payers, hospitals, physicians and radiologists. Our model and analysis focused on the decisions of CT scan investment and usage, as well as financial and health outcomes. Additionally, the model evaluated and optimized incentive mechanisms involving the aforementioned stakeholders. We also analyzed how health care payers should design MSSP incentive policies to maximize social welfare of the patient population. Compared with Chapter 3, Chapter 4 presented an analytical model with four decision-making agents and removed some assumptions in Chapter 3 to better capture the reality and the complexity of the health care system. We analytically showed that, in the scenario

without incentive (i.e., FFS), both primary care physicians and radiologists are incentivized to order excessive imaging tests than the optimal health requires. We also obtained similar findings as in Chapter 3 that MSSP incentives can effectively decrease the test rates and adjust the over-testing behavior. Additionally, we found that a higher sharing percentage induces a more significant reduction in the test rate that an agent chooses. We also gave the condition that categorizes the effect of hospital's CT investment on the optimal test rates chosen by individual providers. From the payer's perspective, we showed that CMS chooses appropriate benchmark region to maximize social welfare based on its desired "WTP for health" value. Nevertheless, CMS needs to be aware that too-strict benchmarks may hurt downstream agents' utilities and discourage those agents from participating in the incentive program in the future.

In the last part of the dissertation, we incorporated temporal component into the hierarchical modeling and developed a two-level, multi-period decision making framework consisting of a patient and a primary care physician. The two agents jointly decide the engagement activities in and the delivery of chronic disease management under the influence of the incentive system. The physician-patient interactions were modeled as a general-sum stochastic game with perfect information and switching control structure. Using a nonlinear program, we computed Nash equilibria or optimal strategies for both players. The Health Belief Model (HBM) was incorporated as our theoretical basis to capture the behavioral aspect of the decision processes.

We illustrated the game-theoretic model by applying it to a case study, the coronary heart disease (CHD) management. The analysis focused on physicians' effort level during clinical encounters and patients' choices of lifestyle and primary care visit. We analyzed the following aspects: the effect of PCP's decision on patient's decisions; the effect of patient's decisions on PCP's decision; the effect of primary care payment and action cost on patient's decisions; the effect of reimbursement on PCP's decision; and the effect of disutility of adverse health outcomes on PCP's decision. We found that patient's and PCP's decisions are interdependent, and that setting an appropriate price range for patient and a reimbursement range for

PCP can create positive incentives. Meanwhile, decreasing action cost barriers for patients, increasing PCP's influence, and increasing physician's health disutility are also effective in improving the chronic disease management.

6.2 Future Work

In the following paragraphs, possible future research directions for the work presented in this dissertation are discussed.

Time and organizational hierarchy are two major dimensions in MSDT models. The models in Chapter 3 and 4 are two and three levels, respectively, but use non-repeated game structure. Future studies can add the temporal component into the model to improve the model's capabilities in capturing dynamic evolution of patient health and the long-term impact of incentives on health care costs and quality. Chapter 5 represents a two-level, multi-period model that contains an infinite stochastic process. It addresses the aforementioned limitation from previous chapters. However, the organizational hierarchy needs to be extended in future work to include more decision makers, such as payer and hospital, to formulate and solve the chronic disease management problem from different angles.

As with all mathematical models of complex socio-technical systems, assumptions are made in our work. Some of these assumptions can be relaxed or removed in future work. For example, we assume rational and noncooperative decision makers, while real-world agents usually have their own risk preferences, and cooperation among agents is also possible. An alternative cooperative and/or risk-averse game structure may be considered, and the issues such as risk premium and information sharing could be discussed. We also assume multi-attribute objective/reward functions for agents. However, different agents may assign different priorities to the attributes and may include different components in their functions. The priorities of the attributes and the types of attributes could be considered in our model extensions. In Chapter 3 and 4, we assume a single form of fee schedule (DRG, FFS, or

MSSP) for agents, whereas in reality the reimbursement is likely to be a mix of payments based on various fee schedules. The influences of multiple incentives should be accounted for in future work. Chapter 5 assumes that patients and physicians both have the perfect information about patient health; while in reality, the true health status of a patient may not be known with certainty. Hence, a POMDP model can better capture this constraint in practices.

It is also desirable to use real-world data to calibrate the MSDT model and gain more practical-relevant insights. All of the models in this dissertation involves the behavioral aspect of agents, such as WTP for health and health utilities. Agents' behavior could be better investigated and modeled based on descriptive decision theory. Claims data from payers and providers can be used to calibrate the models in Chapter 3 and 4. Additionally, some system parameters, such as transition probability matrices in Chapter 5, could be estimated through a combination of empirical and statistical approach.

Chapter 3 and 4 chooses MSSP and ACOs as a motivating example. In practice, public payers such as CMS and private insurers have been exploring and field-testing various innovative payment programs. Future work could choose incentive programs such as bundled payment and pay-for-performance as their motivating examples, and formulate and analyze models accordingly. Chapter 5 uses CHD in the case study. The model could be modified and applied to other chronic disease examples, such as diabetes, obesity, and cancer, to obtain clinical-relevant insights.

Lastly, our MSDT model builds the basis for the analysis of other complex socio-technical systems. For example, MSDT could be applied to the decision-making process of climate policy, where many stakeholders including politicians, lobbyists, industry, and consumers are involved, and their often-conflicting incentives need to be aligned. Other systems with organizational, temporal, informational, and geographical scale interdependencies, such as transportation, manufacturing, and finance, are also interesting fields for future MSDT modeling.

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Appendix A

Appendix for Chapter 4

A.1 Detailed Representation of the UMPs in Section 4.3.1.1

In agent P's UMP, its monetary payoff can be simplified as

$$\begin{aligned}\Pi^{P1}(\theta_P|a_h) &= N_1 \cdot \left\{ \frac{1}{2}(c_{H,A,N} + c_{S,A,N}) - \theta_P \cdot [c_{S,A,N} - \tilde{q}c_{S,I,T} - (1 - \tilde{q})c_{S,I,N}] \right. \\ &\quad \left. + \theta_P^2 \cdot \frac{1}{2}[(c_{S,A,N} - c_{H,A,N}) + (1 - \tilde{q})(c_{H,I,T} - c_{S,I,N}) + \tilde{q}(c_{H,I,N} - c_{S,I,T})] \right\}.\end{aligned}$$

Agent P's health benefit can be simplified as

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

In agent R's UMP, its monetary payoff can be simplified as

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

Agent R's health benefit can be simplified as

$$\begin{aligned}
B^{R2}(\theta_R|a_h) &= N_2 \cdot \left\{ \frac{1}{2}\mu_{H,A,N}(2-r) + \frac{1}{2}\mu_{S,A,N} \cdot r \right. \\
&\quad - \theta_R \cdot \{ r \cdot [\mu_{S,A,N} - \tilde{q}\mu_{S,I,T} - (1-\tilde{q})\mu_{S,I,N}] + (1-r)[\mu_{H,A,N} - \tilde{q}\mu_{H,I,N} - (1-\tilde{q})\mu_{H,I,T}] \} \\
&\quad \left. + \theta_R^2 \cdot \frac{1}{2}r \cdot [(\mu_{S,A,N} - \mu_{H,A,N}) + (1-\tilde{q})(\mu_{H,I,T} - \mu_{S,I,N}) + \tilde{q}(\mu_{H,I,N} - \mu_{S,I,T})] \right\}.
\end{aligned}$$

A.2 Proofs of Lemma 1 and 2

We take the first derivative of the health outcome function $B^{P1}(\theta_P|a_h)$ with respect to θ_P and the first derivative of $B^{R2}(\theta_R|a_h)$ with respect to θ_R . Based on Assumption 1, we have the results in Lemma 1.

Next, we show that the monetary-maximizing rate is always 1 (Lemma 2). For agent P, the first derivative of the monetary payoff function $\Pi^{P1}(\theta_P|a_h)$ with respect to θ_P is

$$\begin{aligned}
\frac{\partial \Pi^{P1}(\theta_P|a_h^H)}{\partial \theta_P} &= -N_1 \cdot [c_{S,A,N} - \tilde{q}c_{S,I,T} - (1-\tilde{q})c_{S,I,N}] \\
&\quad + \theta_P N_1 [(c_{S,A,N} - c_{H,A,N}) + (1-\tilde{q})(c_{H,I,T} - c_{S,I,N}) + \tilde{q}(c_{H,I,N} - c_{S,I,T})].
\end{aligned}$$

Given the monetary payoff preferences $c_{H,I,T} = c_{S,I,T} > c_{H,I,N} = c_{S,I,N} > c_{H,A,N} = c_{S,A,N} = 0$, we make the substitutions: $\Delta c = c_{H,I,T} - c_{H,I,N}$, $\Delta c' = c_{H,I,N} - c_{H,A,N}$. Because $\Delta c > 0$, $\Delta c' > 0$, $\theta_P \in [0, 1]$, we have

$$\frac{\partial \Pi^{P1}(\theta_P|a_h^H)}{\partial \theta_P} = N_1(\Delta c' + \tilde{q}\Delta c) + \theta_P N_1(1 - 2\tilde{q})\Delta c \geq N_1[\Delta c' + (1 - \tilde{q})\Delta c] > 0.$$

The result $\theta_1^{*m} = 1$ is then immediate.

For agent R, its monetary payoff function is: $\Pi^{R1}(\theta_P) + \Pi^{R2}(\theta_R) = N_1 \cdot \theta_P \cdot c_I + N_2 \cdot \theta_R \cdot c_I$.

The monetary-payoff-maximizing rate $\theta_R^{*m} = 1$ is obvious. \square

A.3 Proof of Theorem 1

First, we show that agent P's optimal diagnostic test rate θ_P^* satisfies $\theta_P^{*h} < \theta_P^* \leq 1$.

Denote

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

By Assumption 1, we have the following inequalities: $0 < \theta_P^{*h} = \frac{X_1}{X_2} < 1$, $X_1 < 0$, $X_2 < 0$.

The first derivative of the utility function $U^P(\theta_P|a_h)$ with respect to θ_P is

$$\frac{\partial U^P(\theta_P|a_h)}{\partial \theta_P} = -N_1[c_{S,A,N} - \tilde{q}c_{S,I,T} - (1 - \tilde{q})c_{S,I,N} + \lambda^P X_1] + N_1\theta_P[(1 - 2\tilde{q})(c_{H,I,T} - c_{H,I,N}) + \lambda^P X_2].$$

Given the inequalities $c_{S,A,N} - \tilde{q}c_{S,I,T} - (1 - \tilde{q})c_{S,I,N} < 0$, $(1 - 2\tilde{q})(c_{H,I,T} - c_{H,I,N}) < 0$, $X_1 < 0$, $X_2 < 0$, we have

$$\theta_P^* = \begin{cases} \frac{c_{S,A,N} - \tilde{q}c_{H,I,T} - (1 - \tilde{q})c_{H,I,N} + \lambda^P X_1}{(1 - 2\tilde{q})(c_{H,I,T} - c_{H,I,N}) + \lambda^P X_2}, & \text{if } \frac{c_{S,A,N} - \tilde{q}c_{H,I,T} - (1 - \tilde{q})c_{H,I,N} + \lambda^P X_1}{(1 - 2\tilde{q})(c_{H,I,T} - c_{H,I,N}) + \lambda^P X_2} < 1 \\ 1, & \text{if } \frac{c_{S,A,N} - \tilde{q}c_{H,I,T} - (1 - \tilde{q})c_{H,I,N} + \lambda^P X_1}{(1 - 2\tilde{q})(c_{H,I,T} - c_{H,I,N}) + \lambda^P X_2} \geq 1 \end{cases}.$$

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

By Assumption 1 and the similar reasoning process as above, we have $\theta_R^{*h} < \theta_R^* \leq 1$. \square

A.4 Proof of Theorem 2

For agent P:

Denote

$$X_3 = \mu_{S,A,N} - q\mu_{S,I,T} - (1-q)\mu_{S,I,N},$$

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

By Assumption 1, we have $X_3 < 0$, $X_4 < 0$, $X_3 > X_4$. Denote

$$X_5 = -\delta\mu_{S,I,T} + \delta\mu_{S,I,N},$$

$$X_6 = -\delta(\mu_{H,I,T} - \mu_{S,I,N}) + \delta(\mu_{H,I,N} - \mu_{S,I,T}).$$

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

$$\theta_P^{*h}(a_1) - \theta_P^{*h}(a_2) = \frac{X_3 + X_5}{X_4 + X_6} - \frac{X_3}{X_4} = \frac{X_4X_5 - X_3X_6}{(X_4 + X_6)X_4} > 0.$$

Therefore, when agent H switches from $a_2 = 1$ to $a_1 = 1$, the health-maximizing rate for agent P will increase.

Next we consider the changes in the optimal test rate θ_P^* when agent H switches from $a_2 = 1$ to $a_1 = 1$. Denote

$$X_7 = \frac{c_{S,A,N} - (q + \delta)c_{S,I,T} - (1 - q - \delta)c_{S,I,N} + \lambda^P[\mu_{S,A,N} - (q + \delta)\mu_{S,I,T} - (1 - q - \delta)\mu_{S,I,N}]}{[1 - 2(q + \delta)](c_{H,I,T} - c_{H,I,N}) + \lambda^P[(\mu_{S,A,N} - \mu_{H,A,N}) + (1 - q - \delta)(\mu_{H,I,T} - \mu_{S,I,N}) + (q + \delta)(\mu_{H,I,N} - \mu_{S,I,T})]}.$$

When $\theta_P^*(a_2) < 1$ satisfies, $\theta_P^*(a_1) - \theta_P^*(a_2) > 0$ is equivalent to

$$\begin{cases} X_7 \geq 1 > \theta_P^*(a_2), & \text{if } \theta_P^*(a_1) = 1 \\ X_7 > \theta_P^*(a_2), & \text{if } \theta_P^*(a_1) < 1 \end{cases}.$$

Hence, $\theta_P^*(a_1) - \theta_P^*(a_2) > 0$ is equivalent to: $X_7 - \theta_P^*(a_2) > 0$. Compute this inequality, we obtain the condition Eq. 4.21 in Theorem 2.

For agent R:

Similar to the previous reasoning process, we denote $\theta_R^{*h}(a_2) = \frac{X_8}{X_9}$, $X_8 < 0$, $X_9 < 0$, $X_8 > X_9$; denote $\theta_R^{*h}(a_1) = \frac{X_8+X_{10}}{X_9+X_{11}}$, where

$$\begin{aligned}
X_{10} &= \delta \cdot r \cdot (-\mu_{S,I,T} + \mu_{S,I,N}) + \delta(1-r)(-\mu_{H,I,N} + \mu_{H,I,T}), \\
X_{11} &= \delta \cdot r \cdot (-\mu_{H,I,T} + \mu_{S,I,N} + \mu_{H,I,N} - \mu_{S,I,T}).
\end{aligned}$$

Notice that $X_{10} - X_{11} < 0$, $X_{10} < 0$, $X_{11} < 0$, we have

$$\theta_R^{*h}(a_1) - \theta_R^{*h}(a_2) = \frac{X_8 + X_{10}}{X_9 + X_{11}} - \frac{X_8}{X_9} = \frac{X_9 X_{10} - X_8 X_{11}}{(X_9 + X_{11})X_9} > 0.$$

Therefore, when agent H switches from $a_2 = 1$ to $a_1 = 1$, the health-maximizing rate for agent R will increase.

Next we consider the changes in the optimal test rate θ_R^* when agent H switches from $a_2 = 1$ to $a_1 = 1$. Denote

$$\begin{aligned}
X_{12} &= \\
&\frac{-c_I + \lambda^R \{r \cdot [\mu_{S,A,N} - (q + \delta)\mu_{S,I,T} - (1 - q - \delta)\mu_{S,I,N}] + (1 - r)[\mu_{H,A,N} - (q + \delta)\mu_{H,I,N} - (1 - q - \delta)\mu_{H,I,T}]\}}{\lambda^R \cdot r \cdot [\mu_{S,A,N} - \mu_{H,A,N} + (1 - q - \delta)(\mu_{H,I,T} - \mu_{S,I,N}) + (q + \delta)(\mu_{H,I,N} - \mu_{S,I,T})]}.
\end{aligned}$$

Similarly, we have $\theta_R^*(a_1) - \theta_R^*(a_2) > 0$ equivalent to $X_{12} - \theta_R^*(a_2) > 0$. Next, following the same reasoning process in the health-maximizing rate change proof for agent R, it is easy to check that when agent H switches from $a_2 = 1$ to $a_1 = 1$ and when $\theta_R^*(a_2) < 1$, the optimal test rate θ_R^* will increase. \square

A.5 Proof of Corollary 1

For agent P:

Denote

$$\begin{aligned}
X_{13} &= c_{S,A,N} - \tilde{q}c_{S,I,T} - (1 - \tilde{q})c_{S,I,N}, \\
X_{14} &= (1 - 2\tilde{q})(c_{H,I,T} - c_{H,I,N}), \\
X_{15} &= \lambda^P[\mu_{S,A,N} - \tilde{q}\mu_{S,I,T} - (1 - \tilde{q})\mu_{S,I,N}], \\
X_{16} &= \lambda^P[(\mu_{S,A,N} - \mu_{H,A,N}) + (1 - \tilde{q})(\mu_{H,I,T} - \mu_{S,I,N}) + \tilde{q}(\mu_{H,I,N} - \mu_{S,I,T})].
\end{aligned}$$

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

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

Take the first derivative of θ_P^{**} with respect to α , and we have the inequality

$$\frac{\partial\theta_P^{**}}{\partial\alpha} = \frac{[X_{14}X_{15} - X_{13}X_{16} + (X_{14} + X_{16})(1 + \gamma_p)c_I]\eta}{(X_{14} + X_{16} - X_{14}\eta\alpha)^2} < 0,$$

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

Hence θ_P^{**} is a strict decreasing function of α when $\theta_P^{**} \in (0, 1)$.

For agent R:

Similarly, when $\theta_R^{**} \in (0, 1)$, denote $\theta_R^{**} = \frac{-c_I + \eta\beta(1 + \gamma_p)c_I + X_{17}}{X_{18}}$. By Assumption 1, $X_{17} < 0$, $X_{18} < 0$. Take the first derivative of θ_R^{**} with respect to β , we have the inequality

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

Hence θ_R^{**} is a strict decreasing function of β when $\theta_R^{**} \in (0, 1)$. □

A.6 Proof of Corollary 2

For agent P:

Using the notations in Proof for Corollary 1, we have $\frac{\eta\alpha(1 + \gamma_p)c_I + (1 - \eta\alpha)X_{13} + X_{15}}{(1 - \eta\alpha)X_{14} + X_{16}} \leq \frac{X_{13} + X_{15}}{X_{14} + X_{16}}$, and

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

Recall that $\theta_P^* = \text{Min}\{1, \frac{X_{13}+X_{15}}{X_{14}+X_{16}}\}$. 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 $\frac{X_{13}+X_{15}}{X_{14}+X_{16}} > 1$, $\theta_P^{**} \leq 1 = \theta_P^*$. Hence we always have $\theta_P^{**} \leq \theta_P^*$.

For agent R:

Following the notations in Proof for Corollary 1, we have $\frac{-c_I + \eta\beta(1+\gamma_p)c_I + X_{17}}{X_{18}} \leq \frac{-c_I + X_{17}}{X_{18}}$, and the equality is reached when $\beta = 0$ (by monotonicity).

Recall that $\theta_R^* = \text{Min}\{1, \frac{-c_I + X_{17}}{X_{18}}\}$. 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

A.7 Parameter Values for Numerical Analysis in Section 4.4

Parameter	Value
Investment cost	$k_1 = 200, k_2 = 0$
Maintenance cost	$c^H(s_1) = 10, c^H(s_2) = 5$
Transition probability	$\Pr(s_1 a_1) = 0.9, \Pr(s_2 a_1) = 0.1,$ $\Pr(s_1 a_2) = 0.2, \Pr(s_2 a_2) = 0.8$
Cost coefficient for agent H	$\gamma_c = 3$
Scale factor of payment for agent H	$\gamma_p = 3.5$
Probability of correct imaging diagnosis	$q = 0.9$
Change coefficient	$\delta = 0.05$
Monetary payoff value	$c_{H,I,T} = c_{S,I,T} = 10, c_{H,I,N} = c_{S,I,N} = 5,$ $c_{H,A,N} = c_{S,A,N} = 0, c_I = 5$
Health benefit value	$\mu_{H,A,N} = \mu_{S,I,T} = 10, \mu_{H,I,N} = 9,$ $\mu_{H,I,T} = 8, \mu_{S,A,N} = 0, \mu_{S,I,N} = -1$
Scale factor of the probability of disease	$r = 0.2$
Patient population number	$N_1 = 100, N_2 = 50$
Weighting of attribute health vs. money	$\lambda^H = \lambda^P = \lambda^R = 10$
Incentive share of cost savings	$\eta = 50\%$

Appendix B

Appendix for Chapter 5

B.1 State Transition Probabilities in Section 5.2.4

$$\Pr[(1, B, Hm)|(1, B, Hm), (maintain, home), \phi] = p_{B11},$$

$$\Pr[(2, B, Hm)|(1, B, Hm), (maintain, home), \phi] = p_{B12}, \dots$$

$$\Pr[(H, B, Hm)|(1, B, Hm), (maintain, home), \phi] = p_{B1H},$$

$$\Pr[(H + 1, B, Hs)|(1, B, Hm), (maintain, home), \phi] = p_{B1(H+1)},$$

$$\Pr[(1, B, Hm)|(2, B, Hm), (maintain, home), \phi] = p_{B21},$$

$$\Pr[(2, B, Hm)|(2, B, Hm), (maintain, home), \phi] = p_{B22}, \dots$$

$$\Pr[(H, B, Hm)|(2, B, Hm), (maintain, home), \phi] = p_{B2H},$$

$$\Pr[(H + 1, B, Hs)|(2, B, Hm), (maintain, home), \phi] = p_{B2(H+1)},$$

...

$$\Pr[(1, B, Hm)|(H, B, Hm), (maintain, home), \phi] = p_{BH1},$$

$$\Pr[(2, B, Hm)|(H, B, Hm), (maintain, home), \phi] = p_{BH2}, \dots$$

$$\Pr[(H, B, Hm)|(H, B, Hm), (maintain, home), \phi] = p_{BHH},$$

$$\Pr[(H + 1, B, Hs)|(H, B, Hm), (maintain, home), \phi] = p_{BH(H+1)};$$

$$\Pr[(1, Nb, Hm)|(1, B, Hm), (relapse, home), \phi] = p_{B11},$$

$$\Pr[(2, Nb, Hm)|(1, B, Hm), (relapse, home), \phi] = p_{B12}, \dots$$

$$\Pr[(H, Nb, Hm)|(1, B, Hm), (relapse, home), \phi] = p_{B1H},$$

$$\Pr[(H + 1, Nb, Hs)|(1, B, Hm), (relapse, home), \phi] = p_{B1(H+1)},$$

$$\Pr[(1, Nb, Hm)|(2, B, Hm), (relapse, home), \phi] = p_{B21},$$

$$\Pr[(2, Nb, Hm)|(2, B, Hm), (relapse, home), \phi] = p_{B22}, \dots$$

$$\Pr[(H, Nb, Hm)|(2, B, Hm), (relapse, home), \phi] = p_{B2H},$$

$$\Pr[(H + 1, Nb, Hs)|(2, B, Hm), (relapse, home), \phi] = p_{B2(H+1)},$$

...

$$\Pr[(1, Nb, Hm)|(H, B, Hm), (relapse, home), \phi] = p_{BH1},$$

$$\Pr[(2, Nb, Hm)|(H, B, Hm), (relapse, home), \phi] = p_{BH2}, \dots$$

$$\Pr[(H, Nb, Hm)|(H, B, Hm), (relapse, home), \phi] = p_{BHH},$$

$$\Pr[(H + 1, Nb, Hs)|(H, B, Hm), (relapse, home), \phi] = p_{BH(H+1)};$$

$$\Pr[(1, B, Po)|(1, B, Hm), (maintain, PCP), \phi] = p_{B11},$$

$$\Pr[(2, B, Po)|(1, B, Hm), (maintain, PCP), \phi] = p_{B12}, \dots$$

$$\Pr[(H, B, Po)|(1, B, Hm), (maintain, PCP), \phi] = p_{B1H},$$

$$\Pr[(H + 1, B, Hs)|(1, B, Hm), (maintain, PCP), \phi] = p_{B1(H+1)},$$

$$\Pr[(1, B, Po)|(2, B, Hm), (maintain, PCP), \phi] = p_{B21},$$

$$\Pr[(2, B, Po)|(2, B, Hm), (maintain, PCP), \phi] = p_{B22}, \dots$$

$$\Pr[(H, B, Po)|(2, B, Hm), (maintain, PCP), \phi] = p_{B2H},$$

$$\Pr[(H + 1, B, Hs)|(2, B, Hm), (maintain, PCP), \phi] = p_{B2(H+1)},$$

...

$$\Pr[(1, B, Po)|(H, B, Hm), (maintain, PCP), \phi] = p_{BH1},$$

$$\Pr[(2, B, Po)|(H, B, Hm), (maintain, PCP), \phi] = p_{BH2}, \dots$$

$$\Pr[(H, B, Po)|(H, B, Hm), (maintain, PCP), \phi] = p_{BHH},$$

$$\Pr[(H + 1, B, Hs)|(H, B, Hm), (maintain, PCP), \phi] = p_{BH(H+1)};$$

$$\Pr[(1, Nb, Po)|(1, B, Hm), (relapse, PCP), \phi] = p_{B11},$$

$$\Pr[(2, Nb, Po)|(1, B, Hm), (relapse, PCP), \phi] = p_{B12}, \dots$$

$$\Pr[(H, Nb, Po)|(1, B, Hm), (relapse, PCP), \phi] = p_{B1H},$$

$$\Pr[(H + 1, Nb, Hs)|(1, B, Hm), (relapse, PCP), \phi] = p_{B1(H+1)},$$

$$\Pr[(1, Nb, Po)|(2, B, Hm), (relapse, PCP), \phi] = p_{B21},$$

$$\Pr[(2, Nb, Po)|(2, B, Hm), (relapse, PCP), \phi] = p_{B22}, \dots$$

$$\Pr[(H, Nb, Po)|(2, B, Hm), (relapse, PCP), \phi] = p_{B2H},$$

$$\Pr[(H + 1, Nb, Hs)|(2, B, Hm), (relapse, PCP), \phi] = p_{B2(H+1)},$$

...

$$\Pr[(1, Nb, Po)|(H, B, Hm), (relapse, PCP), \phi] = p_{BH1},$$

$$\Pr[(2, Nb, Po)|(H, B, Hm), (relapse, PCP), \phi] = p_{BH2}, \dots$$

$$\Pr[(H, Nb, Po)|(H, B, Hm), (relapse, PCP), \phi] = p_{BHH},$$

$$\Pr[(H + 1, Nb, Hs)|(H, B, Hm), (relapse, PCP), \phi] = p_{BH(H+1)};$$

$$\Pr[(1, B, Hm)|(1, Nb, Hm), (switch, home), \phi] = p_{Nb11},$$

$$\Pr[(2, B, Hm)|(1, Nb, Hm), (switch, home), \phi] = p_{Nb12}, \dots$$

$$\Pr[(H, B, Hm)|(1, Nb, Hm), (switch, home), \phi] = p_{Nb1H},$$

$$\Pr[(H + 1, B, Hs)|(1, Nb, Hm), (switch, home), \phi] = p_{Nb1(H+1)},$$

$$\Pr[(1, B, Hm)|(2, Nb, Hm), (switch, home), \phi] = p_{Nb21},$$

$$\Pr[(2, B, Hm)|(2, Nb, Hm), (switch, home), \phi] = p_{Nb22}, \dots$$

$$\Pr[(H, B, Hm)|(2, Nb, Hm), (switch, home), \phi] = p_{Nb2H},$$

$$\Pr[(H + 1, B, Hs)|(2, Nb, Hm), (switch, home), \phi] = p_{Nb2(H+1)},$$

...

$$\Pr[(1, B, Hm)|(H, Nb, Hm), (switch, home), \phi] = p_{NbH1},$$

$$\Pr[(2, B, Hm)|(H, Nb, Hm), (switch, home), \phi] = p_{NbH2}, \dots$$

$$\Pr[(H, B, Hm)|(H, Nb, Hm), (switch, home), \phi] = p_{NbHH},$$

$$\Pr[(H + 1, B, Hs)|(H, Nb, Hm), (switch, home), \phi] = p_{NbH(H+1)};$$

$$\Pr[(1, Nb, Hm)|(1, Nb, Hm), (status quo, home), \phi] = p_{Nb11},$$

$$\Pr[(2, Nb, Hm)|(1, Nb, Hm), (status quo, home), \phi] = p_{Nb12}, \dots$$

$$\Pr[(H, Nb, Hm)|(1, Nb, Hm), (status quo, home), \phi] = p_{Nb1H},$$

$$\Pr[(H + 1, Nb, Hs)|(1, Nb, Hm), (status quo, home), \phi] = p_{Nb1(H+1)},$$

$$\Pr[(1, Nb, Hm)|(2, Nb, Hm), (status\ quo, home), \phi] = p_{Nb21},$$

$$\Pr[(2, Nb, Hm)|(2, Nb, Hm), (status\ quo, home), \phi] = p_{Nb22}, \dots$$

$$\Pr[(H, Nb, Hm)|(2, Nb, Hm), (status\ quo, home), \phi] = p_{Nb2H},$$

$$\Pr[(H + 1, Nb, Hs)|(2, Nb, Hm), (status\ quo, home), \phi] = p_{Nb2(H+1)},$$

...

$$\Pr[(1, Nb, Hm)|(H, Nb, Hm), (status\ quo, home), \phi] = p_{NbH1},$$

$$\Pr[(2, Nb, Hm)|(H, Nb, Hm), (status\ quo, home), \phi] = p_{NbH2}, \dots$$

$$\Pr[(H, Nb, Hm)|(H, Nb, Hm), (status\ quo, home), \phi] = p_{NbHH},$$

$$\Pr[(H + 1, Nb, Hs)|(H, Nb, Hm), (status\ quo, home), \phi] = p_{NbH(H+1)};$$

$$\Pr[(1, B, Po)|(1, Nb, Hm), (switch, PCP), \phi] = p_{Nb11},$$

$$\Pr[(2, B, Po)|(1, Nb, Hm), (switch, PCP), \phi] = p_{Nb12}, \dots$$

$$\Pr[(H, B, Po)|(1, Nb, Hm), (switch, PCP), \phi] = p_{Nb1H},$$

$$\Pr[(H + 1, B, Hs)|(1, Nb, Hm), (switch, PCP), \phi] = p_{Nb1(H+1)},$$

$$\Pr[(1, B, Po)|(2, Nb, Hm), (switch, PCP), \phi] = p_{Nb21},$$

$$\Pr[(2, B, Po)|(2, Nb, Hm), (switch, PCP), \phi] = p_{Nb22}, \dots$$

$$\Pr[(H, B, Po)|(2, Nb, Hm), (switch, PCP), \phi] = p_{Nb2H},$$

$$\Pr[(H + 1, B, Hs)|(2, Nb, Hm), (switch, PCP), \phi] = p_{Nb2(H+1)},$$

...

$$\Pr[(1, B, Po)|(H, Nb, Hm), (switch, PCP), \phi] = p_{NbH1},$$

$$\Pr[(2, B, Po)|(H, Nb, Hm), (switch, PCP), \phi] = p_{NbH2}, \dots$$

$$\Pr[(H, B, Po)|(H, Nb, Hm), (switch, PCP), \phi] = p_{NbHH},$$

$$\Pr[(H + 1, B, Hs)|(H, Nb, Hm), (switch, PCP), \phi] = p_{NbH(H+1)};$$

$$\Pr[(1, Nb, Po)|(1, Nb, Hm), (status quo, PCP), \phi] = p_{Nb11},$$

$$\Pr[(2, Nb, Po)|(1, Nb, Hm), (status quo, PCP), \phi] = p_{Nb12}, \dots$$

$$\Pr[(H, Nb, Po)|(1, Nb, Hm), (status quo, PCP), \phi] = p_{Nb1H},$$

$$\Pr[(H + 1, Nb, Hs)|(1, Nb, Hm), (status quo, PCP), \phi] = p_{Nb1(H+1)},$$

$$\Pr[(1, Nb, Po)|(2, Nb, Hm), (status quo, PCP), \phi] = p_{Nb21},$$

$$\Pr[(2, Nb, Po)|(2, Nb, Hm), (status quo, PCP), \phi] = p_{Nb22}, \dots$$

$$\Pr[(H, Nb, Po)|(2, Nb, Hm), (status quo, PCP), \phi] = p_{Nb2H},$$

$$\Pr[(H + 1, Nb, Hs)|(2, Nb, Hm), (status quo, PCP), \phi] = p_{Nb2(H+1)},$$

...

$$\Pr[(1, Nb, Po)|(H, Nb, Hm), (status quo, PCP), \phi] = p_{NbH1},$$

$$\Pr[(2, Nb, Po)|(H, Nb, Hm), (status quo, PCP), \phi] = p_{NbH2}, \dots$$

$$\Pr[(H, Nb, Po)|(H, Nb, Hm), (status quo, PCP), \phi] = p_{NbHH},$$

$$\Pr[(H + 1, Nb, Hs)|(H, Nb, Hm), (status quo, PCP), \phi] = p_{NbH(H+1)};$$

$$\Pr[(1, B, Hm)|(1, B, Po), \phi, high/low] = p_{Po11},$$

$$\Pr[(2, B, Hm)|(1, B, Po), \phi, high/low] = p_{Po12}, \dots$$

$$\Pr[(H, B, Hm)|(1, B, Po), \phi, high/low] = p_{Po1H},$$

$$\Pr[(H + 1, B, Hs)|(1, B, Po), \phi, high/low] = p_{Po1(H+1)},$$

$$\Pr[(1, B, Hm)|(2, B, Po), \phi, high/low] = p_{Po21},$$

$$\Pr[(2, B, Hm)|(2, B, Po), \phi, high/low] = p_{Po22}, \dots$$

$$\Pr[(H, B, Hm)|(2, B, Po), \phi, high/low] = p_{Po2H},$$

$$\Pr[(H + 1, B, Hs)|(2, B, Po), \phi, high/low] = p_{Po2(H+1)},$$

...

$$\Pr[(1, B, Hm)|(H, B, Po), \phi, high/low] = p_{PoH1},$$

$$\Pr[(2, B, Hm)|(H, B, Po), \phi, high/low] = p_{PoH2}, \dots$$

$$\Pr[(H, B, Hm)|(H, B, Po), \phi, high/low] = p_{PoHH},$$

$$\Pr[(H + 1, B, Hs)|(H, B, Po), \phi, high/low] = p_{PoH(H+1)};$$

$$\Pr[(1, B, Hm)|(1, Nb, Po), \phi, high] = p_{Po11} \cdot p_{h,B},$$

$$\Pr[(2, B, Hm)|(1, Nb, Po), \phi, high] = p_{Po12} \cdot p_{h,B}, \dots$$

$$\Pr[(H, B, Hm)|(1, Nb, Po), \phi, high] = p_{Po1H} \cdot p_{h,B},$$

$$\Pr[(H + 1, B, Hs)|(1, Nb, Po), \phi, high] = p_{Po1(H+1)} \cdot p_{h,B},$$

$$\Pr[(1, B, Hm)|(2, Nb, Po), \phi, high] = p_{Po21} \cdot p_{h,B},$$

$$\Pr[(2, B, Hm)|(2, Nb, Po), \phi, high] = p_{Po22} \cdot p_{h,B}, \dots$$

$$\Pr[(H, B, Hm)|(2, Nb, Po), \phi, high] = p_{Po2H} \cdot p_{h,B},$$

$$\Pr[(H + 1, B, Hs)|(2, Nb, Po), \phi, high] = p_{Po2(H+1)} \cdot p_{h,B},$$

...

$$\Pr[(1, B, Hm)|(H, Nb, Po), \phi, high] = p_{PoH1} \cdot p_{h,B},$$

$$\Pr[(2, B, Hm)|(H, Nb, Po), \phi, high] = p_{PoH2} \cdot p_{h,B}, \dots$$

$$\Pr[(H, B, Hm)|(H, Nb, Po), \phi, high] = p_{PoHH} \cdot p_{h,B},$$

$$\Pr[(H + 1, B, Hs)|(H, Nb, Po), \phi, high] = p_{PoH(H+1)} \cdot p_{h,B};$$

$$\Pr[(1, Nb, Hm)|(1, Nb, Po), \phi, high] = p_{Po11} \cdot (1 - p_{h,B}),$$

$$\Pr[(2, Nb, Hm)|(1, Nb, Po), \phi, high] = p_{Po12} \cdot (1 - p_{h,B}), \dots$$

$$\Pr[(H, Nb, Hm)|(1, Nb, Po), \phi, high] = p_{Po1H} \cdot (1 - p_{h,B}),$$

$$\Pr[(H + 1, Nb, Hs)|(1, Nb, Po), \phi, high] = p_{Po1(H+1)} \cdot (1 - p_{h,B}),$$

$$\Pr[(1, Nb, Hm)|(2, Nb, Po), \phi, high] = p_{Po21} \cdot (1 - p_{h,B}),$$

$$\Pr[(2, Nb, Hm)|(2, Nb, Po), \phi, high] = p_{Po22} \cdot (1 - p_{h,B}), \dots$$

$$\Pr[(H, Nb, Hm)|(2, Nb, Po), \phi, high] = p_{Po2H} \cdot (1 - p_{h,B}),$$

$$\Pr[(H + 1, Nb, Hs)|(2, Nb, Po), \phi, high] = p_{Po2(H+1)} \cdot (1 - p_{h,B}),$$

...

$$\Pr[(1, Nb, Hm)|(H, Nb, Po), \phi, high] = p_{PoH1} \cdot (1 - p_{h,B}),$$

$$\Pr[(2, Nb, Hm)|(H, Nb, Po), \phi, high] = p_{PoH2} \cdot (1 - p_{h,B}), \dots$$

$$\Pr[(H, Nb, Hm)|(H, Nb, Po), \phi, high] = p_{PoHH} \cdot (1 - p_{h,B}),$$

$$\Pr[(H + 1, Nb, Hs)|(H, Nb, Po), \phi, high] = p_{PoH(H+1)} \cdot (1 - p_{h,B});$$

$$\Pr[(1, B, Hm)|(1, Nb, Po), \phi, low] = p_{Po11} \cdot (1 - p_{l,Nb}),$$

$$\Pr[(2, B, Hm)|(1, Nb, Po), \phi, low] = p_{Po12} \cdot (1 - p_{l,Nb}), \dots$$

$$\Pr[(H, B, Hm)|(1, Nb, Po), \phi, low] = p_{Po1H} \cdot (1 - p_{l,Nb}),$$

$$\Pr[(H + 1, B, Hs)|(1, Nb, Po), \phi, low] = p_{Po1(H+1)} \cdot (1 - p_{l,Nb}),$$

$$\Pr[(1, B, Hm)|(2, Nb, Po), \phi, low] = p_{Po21} \cdot (1 - p_{l,Nb}),$$

$$\Pr[(2, B, Hm)|(2, Nb, Po), \phi, low] = p_{Po22} \cdot (1 - p_{l,Nb}), \dots$$

$$\Pr[(H, B, Hm)|(2, Nb, Po), \phi, low] = p_{Po2H} \cdot (1 - p_{l,Nb}),$$

$$\Pr[(H + 1, B, Hs)|(2, Nb, Po), \phi, low] = p_{Po2(H+1)} \cdot (1 - p_{l,Nb}),$$

...

$$\Pr[(1, B, Hm)|(H, Nb, Po), \phi, low] = p_{PoH1} \cdot (1 - p_{l,Nb}),$$

$$\Pr[(2, B, Hm)|(H, Nb, Po), \phi, low] = p_{PoH2} \cdot (1 - p_{l,Nb}), \dots$$

$$\Pr[(H, B, Hm)|(H, Nb, Po), \phi, low] = p_{PoHH} \cdot (1 - p_{l,Nb}),$$

$$\Pr[(H + 1, B, Hs)|(H, Nb, Po), \phi, low] = p_{PoH(H+1)} \cdot (1 - p_{l,Nb});$$

$$\Pr[(1, Nb, Hm)|(1, Nb, Po), \phi, low] = p_{Po11} \cdot p_{l,Nb},$$

$$\Pr[(2, Nb, Hm)|(1, Nb, Po), \phi, low] = p_{Po12} \cdot p_{l,Nb}, \dots$$

$$\Pr[(H, Nb, Hm)|(1, Nb, Po), \phi, low] = p_{Po1H} \cdot p_{l,Nb},$$

$$\Pr[(H + 1, Nb, Hs)|(1, Nb, Po), \phi, low] = p_{Po1(H+1)} \cdot p_{l,Nb},$$

$$\Pr[(1, Nb, Hm)|(2, Nb, Po), \phi, low] = p_{Po21} \cdot p_{l,Nb},$$

$$\Pr[(2, Nb, Hm)|(2, Nb, Po), \phi, low] = p_{Po22} \cdot p_{l,Nb}, \dots$$

$$\Pr[(H, Nb, Hm)|(2, Nb, Po), \phi, low] = p_{Po2H} \cdot p_{l,Nb},$$

$$\Pr[(H + 1, Nb, Hs)|(2, Nb, Po), \phi, low] = p_{Po2(H+1)} \cdot p_{l,Nb},$$

...

$$\Pr[(1, Nb, Hm)|(H, Nb, Po), \phi, low] = p_{PoH1} \cdot p_{l,Nb},$$

$$\Pr[(2, Nb, Hm)|(H, Nb, Po), \phi, low] = p_{PoH2} \cdot p_{l,Nb}, \dots$$

$$\Pr[(H, Nb, Hm)|(H, Nb, Po), \phi, low] = p_{PoHH} \cdot p_{l,Nb},$$

$$\Pr[(H + 1, Nb, Hs)|(H, Nb, Po), \phi, low] = p_{PoH(H+1)} \cdot p_{l,Nb};$$

$$\Pr[(1, B, Hm)|(H + 1, B, Hs), \phi, \phi] = p_{Hs(H+1)1},$$

$$\Pr[(2, B, Hm)|(H + 1, B, Hs), \phi, \phi] = p_{Hs(H+1)2}, \dots$$

$$\Pr[(H, B, Hm)|(H + 1, B, Hs), \phi, \phi] = p_{Hs(H+1)H},$$

$$\Pr[(H + 1, B, Hs)|(H + 1, B, Hs), \phi, \phi] = p_{Hs(H+1)(H+1)};$$

$$\Pr[(1, Nb, Hm)|(H + 1, Nb, Hs), \phi, \phi] = p_{Hs(H+1)1},$$

$$\Pr[(2, Nb, Hm)|(H + 1, Nb, Hs), \phi, \phi] = p_{Hs(H+1)2}, \dots$$

$$\Pr[(H, Nb, Hm)|(H + 1, Nb, Hs), \phi, \phi] = p_{Hs(H+1)H},$$

$$\Pr[(H + 1, Nb, Hs)|(H + 1, Nb, Hs), \phi, \phi] = p_{Hs(H+1)(H+1)}.$$

B.2 Reward Functions in Section 5.2.5

Agent PA's reward functions are

$$r^{PA}[(h, B, Hm), (maintain, home), \phi] = u^{PA}(h) - c_1^{PA},$$

$$r^{PA}[(h, B, Hm), (relapse, home), \phi] = u^{PA}(h),$$

$$r^{PA}[(h, B, Hm), (maintain, PCP), \phi] = u^{PA}(h) - c_1^{PA},$$

$$r^{PA}[(h, B, Hm), (relapse, PCP), \phi] = u^{PA}(h),$$

$$r^{PA}[(h, Nb, Hm), (switch, home), \phi] = u^{PA}(h) - c_2^{PA},$$

$$r^{PA}[(h, Nb, Hm), (status\ quo, home), \phi] = u^{PA}(h),$$

$$r^{PA}[(h, Nb, Hm), (switch, PCP), \phi] = u^{PA}(h) - c_2^{PA},$$

$$r^{PA}[(h, Nb, Hm), (status\ quo, PCP), \phi] = u^{PA}(h),$$

$$r^{PA}[(h, l, Po), \phi, high] = u^{PA}(h) - m_1^{PA},$$

$$r^{PA}[(h, l, Po), \phi, low] = u^{PA}(h) - m_2^{PA},$$

$$r^{PA}[(H + 1, l, Hs), \phi, \phi] = u^{PA}(H + 1) - m_{Hs}^{PA}.$$

Agent PCP's reward functions are

$$r^{PCP}[(h, l, Hm), a^{PA}, \phi] = 0,$$

$$r^{PCP}[(h, l, Po), \phi, high] = n_1^{PCP},$$

$$r^{PCP}[(h, l, Po), \phi, low] = n_2^{PCP},$$

$$r^{PCP}[(H + 1, l, Hs), \phi, \phi] = -u_{Hs}^{PCP}.$$

B.3 ACC-AHA Stage and NYHA Classification of CHD in Section 5.4.1

ACC-AHA Stage	NYHA Functional Classification
A At high risk for heart failure but without structural heart disease or symptoms of heart failure (e.g., patients with hypertension or coronary artery disease)	None
B Structural heart disease but without symptoms of heart failure	I Asymptomatic
C Structural heart disease with prior or current symptoms of heart failure	II Symptomatic with moderate exertion
	III Symptomatic with minimal exertion
D Refractory heart failure requiring specialized interventions	IV Symptomatic at rest

B.4 Assumptions of Numerical Values in Section 5.4.1

Original transition probability data in literature [154]

With medical treatment	NYHA I	NYHA II	NYHA III	NYHA IV
NYHA I	0.7956	0.1245	0.0738	0.0061
NYHA II	0.0710	0.8448	0.0765	0.0077
NYHA III	0.0047	0.0893	0.8845	0.0216
NYHA IV	0.0000	0.1064	0.1064	0.7872

Transition probability data mapped in ACC-AHA system

With medical treatment	ACC-AHA A	ACC-AHA B	ACC-AHA C	ACC-AHA D
ACC-AHA A	0.95	0.05	0.00	0.00
ACC-AHA B	0.04	0.76	0.19	0.01
ACC-AHA C	0.00	0.04	0.95	0.01
ACC-AHA D	0.00	0.00	0.21	0.79

Transition probability data adjusted for \mathcal{H}_B

Without medical treatment, beneficial lifestyle	ACC/AHA A	ACC/AHA B	ACC/AHA C	ACC/AHA D	Of baseline
ACC/AHA A	0.93	0.07	0.00	0.00	-2%
ACC/AHA B	0.04	0.72	0.23	0.01	-5%
ACC/AHA C	0.00	0.04	0.86	0.10	-10%

Transition probability data adjusted for \mathcal{H}_{Nb}

Without medical treatment, non-beneficial lifestyle	ACC/AHA A	ACC/AHA B	ACC/AHA C	ACC/AHA D	Of baseline
ACC/AHA A	0.90	0.10	0.00	0.00	-5%
ACC/AHA B	0.04	0.68	0.27	0.01	-10%
ACC/AHA C	0.00	0.03	0.81	0.16	-15%

Original health utility data in literature

NYHA Stage	Göhler et al., 2009[155]	Kourlaba et al., 2014[156]	Yao et al., 2007[154]
I	0.90	0.82	0.82
II	0.83	0.74	0.72
III	0.74	0.64	0.59
IV	0.60	0.17	0.51

Health utility data mapped in ACC-AHA system

NYHA Stage	ACC-AHA stage	Health utility	Note
	A	1.00	Defined according to ACC-AHA descriptions
I	B	0.85	$= (0.90 + 0.82 + 0.82) / 3$
II	C	0.71	$= (0.83 + 0.74 + 0.72 + 0.74 + 0.64 + .59) / 6$
III			
IV	D	0.43	$= (0.60 + 0.46 - 0.29 + 0.51) / 3$