

**GAME THEORY AND MECHANISM DESIGN FOR COOPERATIVE
COMPETITION DILEMMAS BETWEEN HEALTHCARE PROVIDERS**

A Dissertation Presented

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ABSTRACT

Cooperation among healthcare providers should be encouraged to achieve the public health benefits of efficient coordination, yet natural competition in healthcare markets often creates incentive to choose strategies that favor the individual provider. This conflict can interfere with the ideal of coordinated care when less efficient solutions add to rising healthcare costs. National health spending reached \$2.8 trillion in 2012 and is expected to exceed 20% of the United States gross domestic product by 2022, while an estimated one-third of healthcare spending is waste including \$190 billion due to overtreatment and \$160 billion due to failures of care delivery and care coordination.

This dissertation extends the application of game theory models in healthcare to characterize the effects of such market failures and proposes mechanism design solutions to discourage overtreatment and promote care coordination for three example applications. The developed underlying mathematical models create a general framework to help providers, payors, and policymakers understand healthcare market dynamics, while the example applications ground this research with actionable recommendations to improve quality and reduce costs in real-world scenarios.

Chapter 2 develops a commons dilemma model to characterize antibiotic prescribing behavior and proposes three alternate approaches (collective cooperative management,

use taxes, and resistance penalties) to promote appropriate use in stewardship efforts. Chapter 3 develops a volunteer's dilemma model to characterize the potential for care coordination failures in accountable care organizations, proposes three economic mechanisms that can help ensure patients receive indicated care, and explores possible outcomes of a mixed strategy equilibrium for a time-dynamic extension. Chapter 4 presents a fair division application to design effective incentives between a payor and a contracted healthcare provider (here a skilled nursing facility), developing a chance constrained programming model to identify the optimal split of shared savings to incentivize improved quality and an assignment algorithm to determine the maximum payment for higher performing facilities that accept more patients. Finally, Chapter 5 discusses the practical implications of this work, potential limitations of these models, and possible extensions.

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Chapter 1. Introduction

1.1. Healthcare Markets in the United States

Cooperation among healthcare providers should be encouraged to achieve the public health benefits of efficient coordination, yet natural competition in healthcare markets often creates incentives to choose strategies that favor the individual provider. This conflict can interfere with the ideal state of coordinated care when less efficient solutions contribute to rising costs. National health spending reached \$2.8 trillion in 2012 [1] and is expected to exceed 20% of the United States gross domestic product by 2022 [2].

Although this spending is twice as much as the average per capita expenditures of other developed countries, the United States ranks in the lowest third in life expectancy, obesity, and supply of doctors [3].

In 2013, Berwick and Hackbart estimated one-third of health spending is waste [4], attributing an estimated \$190 billion waste to overtreatment [5-8] and \$160 billion waste to failures of care delivery and care coordination [5-7, 9-11]. The established incentives lead rational providers to overtreatment with certain care and failures to coordinate other forms of care. We apply game theory models to characterize how such market failures lead to suboptimal equilibria in healthcare applications and propose mechanism design solutions to realign incentives towards sustainable cooperative equilibria.

The Patient Protection and Affordable Care Act, signed into law in 2010, drives current healthcare reform efforts and addresses market failures by promoting value-based payments over traditional fee-for-service models. The U.S. Department of Health and Human Services “set a goal of tying 50 percent of Medicare payments to quality or value through alternative payment models, such as Accountable Care Organizations (ACOs) or bundled payment arrangements” by the end of 2018 [12]. One prediction suggests ACOs, described by the Centers for Medicare and Medicaid Services [13] as “groups of doctors, hospitals, and other healthcare providers, who come together voluntarily to give coordinated high quality care,” will cover approximately 50 million people by 2018 and 150 million by 2025 [14]. As more and more providers may enter into such cooperative arrangements, it is important to define the practices that lead to stable partnerships that promote public health and allow for a sustainable business model. The benefits of such a coalition are intuitive, but Ford et al. [15] found that like-minded healthcare coalitions are undone in part by ambiguous contract agreements. The ACO offers structure to the models, but our conclusions herein may extend to cooperative competition applications among providers in other contexts.

The goals of this study are directed by the Institute for Healthcare Improvement Triple Aim [16] to improve patient experience, improve population health, and reduce per capita costs. With awareness that commons dilemmas result in overtreatment and inefficient allocation of resources, strategies can be developed to reduce the per capita cost of care. Research into the volunteer’s dilemmas that lead to failures in care delivery and care coordination will provide insight into how to enhance the patient experience of care. And

in the broadest terms, our mathematical models to achieve fair division of services among providers are designed to limit pricing failures and improve the health of the population.

1.2. General Model

We developed a generalized mathematical model to describe commons dilemmas and volunteer's dilemmas that arise with the interactions among a network of providers, supposing provider j chooses some strategy s_j in the provision of a specified resource that maximizes their utility formulation $U_j(s_j)$, or

$$s_j = \operatorname{argmax}_{s_j} (U_j(s_j)).$$

Assuming each provider considers this resource in the context of a defined provider network, the total provision is determined by summing across all provider strategies

$$\sum_j s_j = \sum_j \operatorname{argmax}_{s_j} (U_j(s_j)).$$

Letting R^* denote the ideal level at which the resource is provided such that $\sum_j s_j = R^*$ in the social optimum, the strategy s_j can be normalized to describe a share relative to R^* such that $0 \leq s_j \leq 1$ and $R^* = 1$. Letting $S = \{s_1, \dots, s_j, \dots, s_N\}$ denote the strategy set for a network of N providers, provider j 's utility-maximizing strategy s_j is dependent on the strategy of other providers such that

$$s_j = \operatorname{argmax}_{s_j} (U_j(s_j | S)).$$

Commons dilemmas address appropriation problems in which providers are incentivized to overuse the resource such that $\sum_j s_j > R^*$. Volunteer's dilemmas address provision

problems in which providers are not sufficiently incentivized to supply the resource as needed such that $\sum_j s_j < R^*$. Fair division addresses how to divide resource shares to identify a solution that appeals to all providers such that $\sum_j s_j \approx R^*$. Suppose there is an incentive designer who can realign incentives by introducing a utility function

$U_j(s_j) = U^*(s_j) \forall j$ to minimize the difference between the original outcome and the ideal provision level, or

$$\min_{U^*} \left(\sum_j \operatorname{argmax}_{s_j} (U^*(s_j | S)) - R^* \right).$$

This designer need not be an outside central authority, as providers could collectively agree to alternate incentives if it is deemed mutually beneficial. Provider j should agree to change from U_j to U^* if

$$U^*(s_j^*) > U_j(s_j),$$

where

$$s_j^* = \operatorname{argmax} (U^*(s_j^* | S)).$$

Our definition of provider utility includes non-monetary benefits and costs (referred to as “psychic” benefits and costs in the economic literature), in addition to strictly monetary measurements. For example, the moral appeal to provide quality care may be a psychic benefit, while the opportunity cost of additional time needed for such care may represent a psychic cost. Although their inclusion complicates quantitative evaluation, it allows for a more comprehensive interpretation of incentives.

1.3. Research Contribution

Table 1-1 summarizes the literature on game theory applications in healthcare, differentiating between conceptual editorials written by medical professionals and more rigorous applications from academic researchers. After reviewing the literature, we identified an opportunity to develop mathematical models to extend the application of game theory in healthcare beyond analogy. We learn from the framework laid out by Roth [17] for the “economist as engineer” to propose mechanism design solutions to impact the quality and cost of healthcare in a real-world scenario. We developed three applications and addressed the following research questions to demonstrate the implementation and impact of this approach:

1. Why do providers continue to overprescribe antibiotics and what incentive changes would motivate them to comply with best practice guidelines?
2. Why does an accountable care organization underperform on a process measure such as interventions to prevent readmissions and what mechanisms could be introduced to motivate providers to conduct all indicated interventions?
3. How can a payor design a value-based contract that rewards skilled nursing facilities providing quality care at a lower cost?

The underlying mathematical models create a general framework to help providers, payors, and policymakers understand healthcare market dynamics, while the example applications ground this research with actionable recommendations to improve quality and reduce costs in real-world scenarios. All might be extended to related applications such as the examples listed in Table 1-2.

Table 1-1. Review of publications on game theory in healthcare

Editorials for medical professionals	Academic research
<ul style="list-style-type: none"> • Medical decision making for liver biopsies [18] • Vaccinating surgical residents [19] • Funding for cancer research [20] and biomedical research [21] • Therapeutic alliance in psychoanalytic treatment [22] • Negotiation between surgeons and managed-care companies [23] • Operating room and hospital management [24-28] • Decision-making for gastroenterologists [29-31] and neurosurgeons [32] • Medical ethics of disconnecting patients from respirators [33] • Invasive tumor metabolism [34] • Managing physical therapy resources [35] • The state of nursing research [36] • Matching urology residency applicants to programs [37] 	<ul style="list-style-type: none"> • Valvular heart disease diagnosis [38] • Matching residents in the labor market [39] • Transplant kidney exchanges [40, 41] • Public health legislation banning smoking [42] • The physician-patient relationship in a medical consultation [43-45] • Cooperation in a community-based mental health coalition [15] • Tumor growth as an evolutionary game [46-49] • Hospital stockpiling of medical supplies prior to a disaster [50] • Chinese healthcare reform [51] • Overcrowding in the emergency department [52] and walk-in clinics [53] • The effect of incentives on influenza vaccination behavior [54] • Healthcare system price inflation [55] • Pediatric vaccine market pricing [56] • Readmissions public policy [57]

Table 1-2. Examples of commons dilemma, volunteer's dilemma, and fair division applications in healthcare

Category	Micro level (within systems)	Macro level (between systems)
<i>Commons Dilemma</i>	<ul style="list-style-type: none"> • Inventory sharing • Imaging test utilization 	<ul style="list-style-type: none"> • Antibiotic stewardship • Organ transplant networks
<i>Volunteer's Dilemma</i>	<ul style="list-style-type: none"> • Post-discharge interventions • Patient handoffs 	<ul style="list-style-type: none"> • Infection control • Treating uninsured patients
<i>Fair Division</i>	<ul style="list-style-type: none"> • Financial incentive distributions • Shift scheduling 	<ul style="list-style-type: none"> • Value-based contracts • Market segmentation

The remainder of this dissertation is organized as follows: Chapter 2 develops a commons dilemma model to characterize antibiotic prescribing behavior and proposes three alternate approaches (collective cooperative management, use taxes, and resistance penalties) to promote appropriate use in stewardship efforts. Chapter 3 develops a volunteer's dilemma model to characterize the potential for care coordination failures in accountable care organizations, proposes three economic mechanisms that can help ensure patients receive indicated care, and explores possible outcomes of a mixed strategy equilibrium for a time-dynamic extension. Chapter 4 presents a fair division application to design effective incentives between a payor and a contracted healthcare provider (here a skilled nursing facility), developing a chance constrained programming model to identify the optimal split of shared savings to incentivize improved quality and an assignment algorithm to determine the maximum payment for higher performing facilities that accept more patients. Finally, Chapter 5 discusses the practical implications of this work, potential limitations of these models, and possible extensions.

Chapter 2. Commons Dilemmas in Resource Stewardship to Prevent Antibiotic Resistance

2.1. Introduction

While recent reports from the Centers for Disease Control and Prevention (CDC) [58] and the World Health Organization [59] warned of imminent threats from an observed increase of antibiotic resistance, the problem of antibiotic resistance has been identified as a crisis for over 20 years [60, 61]. The CDC estimated that antibiotic-resistant infections cause over 20 thousand deaths and up to \$20 billion in excess direct healthcare costs annually in the United States alone [58, 62] and called for better coordination between healthcare facilities in antibiotic stewardship efforts [63, 64]. Partly in response, the Obama administration announced the \$1.2 billion *National Action Plan for Combating Antibiotic-Resistant Bacteria* in 2015 [65], outlining steps to increase surveillance of resistant bacteria and antibiotic use, regulate agricultural antibiotic use, develop new antibiotics or alternate therapeutics, and improve international collaboration. The National Action Plan (NAP) also provides federal support for statewide antibiotic stewardship programs to reduce inappropriate antibiotic use locally by 20% in inpatient settings and 50% in outpatient settings by 2020.

Antibiotics are "societal drugs" [66, 67]: Physicians motivated by a desire to serve their patients can create resistant bacteria that spread within a healthcare facility or community through direct and indirect contact [68-72], affecting adversely all patients and providers (Figure 2-1). In this scenario, each provider implicitly weighs the immediate and direct benefits versus the gradual and diffused consequences from prescribing, akin to a "tragedy of the commons." [73]

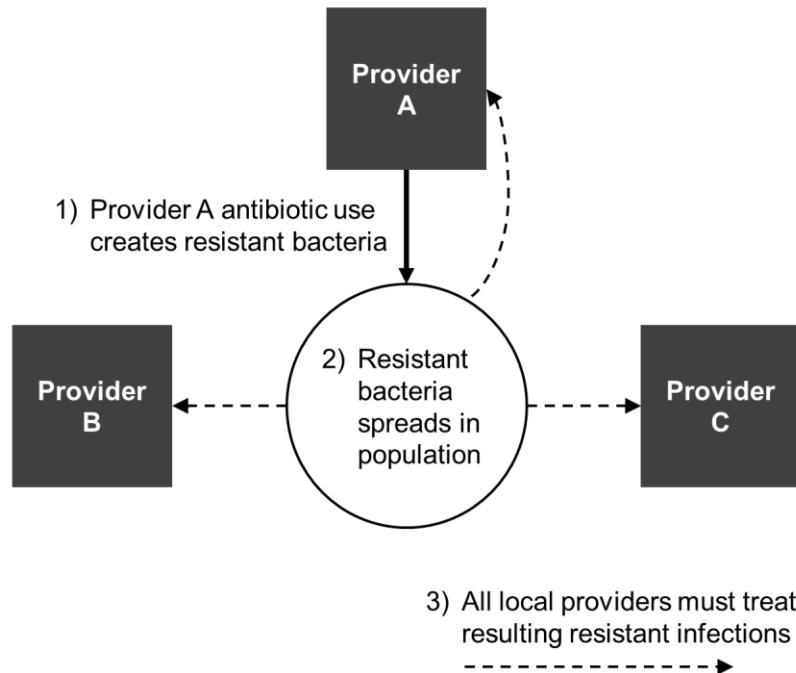


Figure 2-1. Illustration of individual antibiotic use creating resistant bacteria that spread across a local population

Hardin explained this type of tragedy with a metaphor about a common pasture shared by a community of herders, for which each herder's individual incentive to add another cow results in more grazing than the pasture can support and the depletion of this resource over time for everyone. Concluding "freedom in a commons brings ruin to all," Hardin

proposed instead some form of regulation be imposed such as privatization to restrict rights to use the resource or central authority intervention to regulate resource use. In contrast Ostrom [74], winner of the Nobel Prize for her work in economic governance, proposed eight design principles for effective cooperative management of common-pool resources. After some background on antibiotic resistance and stewardship efforts, we therefore develop a mathematical model of antibiotic prescribing practices to more explicitly explore how a commons tragedy can arise. We then suggest how Ostrom's design principles could be used to mediate antibiotic use and how a government use fee policy could be developed to produce an appropriate incentive system to achieve the National Action Plan objectives.

2.2. Literature Review

2.2.1. Antibiotic Resistance and Stewardship

Antimicrobial resistance occurs when microbes develop resistance to an antimicrobial agent, which renders the antimicrobial agent ineffective in treating an infection caused by antimicrobial-resistant microbes. The categorization of antimicrobial resistance includes resistance to antibiotics, antivirals, antifungals, and antiparasitics. We focus on antibiotic resistance, although our conclusions may extend to similar applications for other categories of antimicrobial resistance.

Evidence of resistance to penicillin was observed as early as 1940 [75], shortly before penicillin was first used to treat an infection in a human patient in 1941. Several studies in the early 1940s confirmed that exposure to penicillin created bacterial resistance to

penicillin [76-84]. By 1946, 60% of Staphylococcal infection samples tested in a United Kingdom study exhibited resistance to penicillin [85]. New antibiotics were developed that were initially effective in treating infections, but resistance to those antibiotics emerged soon after [86, 87]. In 1960, a test of *Staphylococcus aureus* strains revealed resistance to all six tested antibiotics, while 30% of the samples exhibited resistance to four or more antibiotics [88]. Figure 2-2 illustrates this pattern, tracking the introduction of major antibiotics and the first evidence of resistance. Although the lost treatment value for older antibiotics has been mitigated by the development of new antibiotics, Figure 2-3 shows how the introduction of new antibiotics has slowed over time, suggesting that the exhaustion of older antibiotics may outpace the development of new antibiotics.

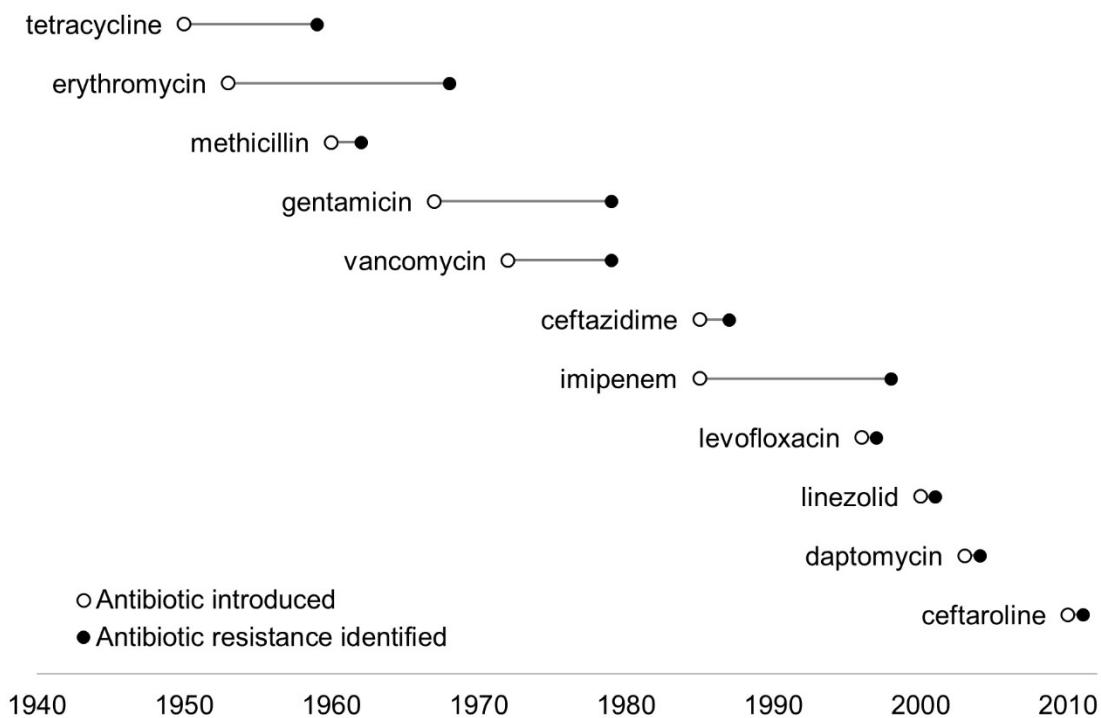


Figure 2-2. Timeline of antibiotic introduction and first observed resistance [58]

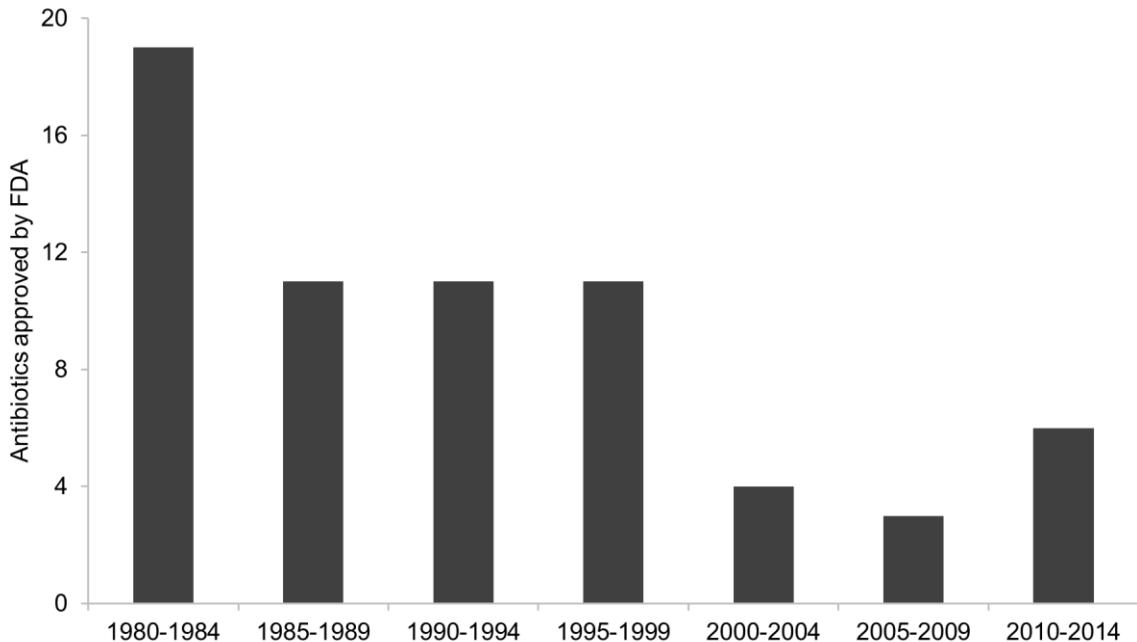


Figure 2-3. New antibiotics approved by the Food and Drug Administration (FDA) from 1980-2014 [89]

Antibiotic stewardship is a crucial practice that can slow the growth of antibiotic resistance by reducing inappropriate use. A systematic review assessing the effects of appropriate empirical antibiotic treatment found that 46.5% of patients were given inappropriate empirical antibiotic treatment [90]. Likewise, a meta-analysis of pediatric studies estimated that the appropriate rate of antibiotic prescriptions for acute respiratory tract infection (primarily a viral condition) is 27.4%, yet physicians actually prescribed antibiotics for 56.9% of acute respiratory tract infection encounters [91]. Although the CDC and National Committee for Quality Assurance recommend that antibiotics are not prescribed for acute bronchitis, the overall antibiotic prescription rate for acute bronchitis encounters remains over 70% [92]. Several studies suggest that physicians are more likely to prescribe inappropriate antibiotics when they believe the patient wants

antibiotics, yet physicians often incorrectly interpret patient expectations [93-96]. While there is some evidence that antibiotic stewardship programs can be financially self-sustaining and improve patient care [97-102], inappropriate use where antibiotics are not clearly indicated remains widespread, suggesting that perceived benefits of prescribing antibiotics outweigh perceived costs.

2.2.2. Tragedy of the Commons

The problem of how an individual uses an unregulated common-pool resource was first discussed by Lloyd [103] and Gordon [104] before it became more widely known as Hardin's tragedy of the commons [73]. The commons dilemma can also be viewed as an n -player extension of the 2-player prisoner's dilemma, first developed by Flood and Drescher [105, 106] to describe a scenario where both players defect in the Nash equilibrium even though the players are better off if both cooperate. Fortunately, experimental evidence [107-111] shows that players manage to cooperate in prisoner's dilemma, especially in repeated games.

Hardin contrasts the tragedy of the commons with Smith's [112] notion in which the individual seeking his own interest is "led by an invisible hand" to promote the public interest and Anderson [113] confirmed with a formal dynamic model that there is no technical solution to the tragedy of the commons under Hardin's assumptions. Feeny et al. [114], however, later found many examples of sustainable management of communal property [115-121]. Ostrom crystallized the lessons learned from such case studies into eight design principles for cooperative arrangements [74].

While the commons analogy often is applied to ecological sustainability topics, Hiatt [122] and more recently Berwick [16, 123] proposed its applicability to healthcare resource utilization issues such as diagnostic tests, disease prevention programs, and medical technologies. The commons framework also has been associated with antibiotic resistance conceptually [124-126] and has guided the development of epidemiological models addressing the role of antibiotic access and infection control strategies in the spread of resistance [127-130]. In a cross-sectional study, 96% of surveyed infectious disease professionals believe antibiotic use could produce a commons tragedy under certain circumstances [131].

2.3. Characterizing Prescribing Behavior

2.3.1. Model Formulation

To develop a utility-maximization model of prescribing a given antibiotic within a regional network of N healthcare organizations, we assume each organization endorses specific guidelines for antibiotic prescribing for their physicians to follow. For instance, an organization's stewardship program may limit inappropriate prescriptions through preauthorizations and prospective audit [132], although in practice there still may be significant intra-organization prescribing variation. Using the notation in Table 2-1, we characterize prescribing behavior with a utility formulation based on inherent benefits and costs. For example, in addition to the infection prevention value, providers also may be influenced by patient insistence [93-96], decision fatigue [133], and potential regret of not prescribing [134].

Table 2-1. Notation for utility-maximization commons model of provider antibiotic prescribing behavior

Variable	Definition
s_j	Prescribing threshold of provider j
$b_j(s_j)$	Benefit to provider j of prescribing an antibiotic at threshold s_j
$c_j(s_j)$	Cost to provider j to purchase an antibiotic at threshold s_j
$d_j(s_j)$	Total cost of the harm of resistant infections that develop due to provider j prescribing at threshold s_j
p_{jk}	The share of $d_k(s_k)$ that provider j incurs where $d_k(s_k)$ is the cost of resistant infections due to provider k prescribing at threshold s_k
q_j	Stewardship moral accountability assumed by provider j , where $0 \leq q_j \leq 1$ represents a weight provider j places on her caused resistance costs $d_j(s_j)$

The prescribing threshold of provider j , s_j , can be conceptualized as a point along a continuum equating to a percentage of candidate patients that are prescribed antibiotics, where candidate patients can include both appropriate and inappropriate indications. If $s_j = 1$ provider j prescribes antibiotics for all candidate patients, whereas if $s_j = 0$ provider j never prescribes. If all candidate patients are ordered from greatest to least marginal benefit, the prescribing threshold can serve as a simple proxy for a stewardship threshold, as illustrated in Figure 2-4. Thus, higher s_j implies the provider is less selective and sometimes prescribes antibiotics when they are not clinically indicated.

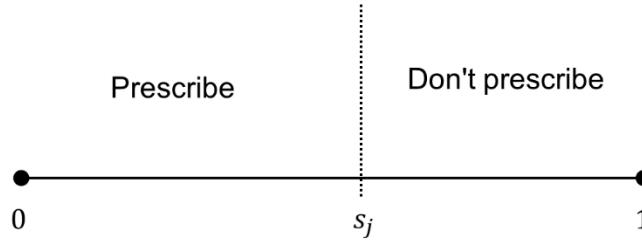


Figure 2-4. Decision continuum for provider j 's prescribing threshold, $0 \leq s_j \leq 1$, for which all candidate patients are ordered from greatest to least marginal benefit

Since the ideal prescribing threshold depends on patient mix, two providers following identical stewardship guidelines may differ in prescribing threshold if their pools of candidate patients are significantly different. For the scope of this chapter, however, we assume that patient mix is identical for all providers such that if provider j and provider k both prescribe at the threshold s_* then the resulting prescribing benefits, $b_j(s_*) = b_k(s_*)$, are equal. We also assume:

- The marginal benefit of prescribing an antibiotic decreases as the prescribing threshold s_j increases such that $b_j(s_j) = s_j^B \forall j$, where the exponent $B \in (0, 1)$ is a constant that determines the shape of the benefit function,
- Prescription costs $c_j(s_j)$ and resistance costs $d_j(s_j)$ are proportional to the prescribing threshold s_j and the same for all providers such that $c_j(s_j) = Cs_j$ and $d_j(s_j) = Ds_j \forall j$, where the coefficients $C > 0$ and $D > 0$ are constants that determine the slope of the cost functions, and
- B , C , and D are constants known to and identical for all providers.

2.3.2. Analytical Results

The utility to provider j of choosing prescribing threshold s_j given benefit $b_j(s_j)$, prescription costs $c_j(s_j)$, and resistance costs $d_j(s_j)$ —or equivalently s_j^B , Cs_j , and Ds_j —then is

$$\begin{aligned} U_j(s_j) &= b_j(s_j) - c_j(s_j) - \sum_k p_{jk} d(s_k) \\ &= s_j^B - Cs_j - p_{jj} Ds_j - \sum_{k \neq j} p_{jk} Ds_k, \end{aligned} \quad (2-1)$$

where $0 \leq p_{jk} \leq 1 \forall k$ represents provider j 's incurred share of resistance costs produced by provider k and p_{jj} is the share of resistance costs both produced and incurred by provider j . Setting the derivative of this utility formulation with respect to s_j to zero produces

$$\frac{\partial U_j}{\partial s_j} = Bs_j^{B-1} - C - p_{jj}D \equiv 0,$$

which solving to find the prescribing threshold that maximizes provider utility produces

$$s_j = \underset{s_j}{\operatorname{argmax}} U_j(s_j) = \left(\frac{C + p_{jj}D}{B} \right)^{\frac{1}{B-1}}. \quad (2-2)$$

To restrict $\underset{s_j}{\operatorname{argmax}} U_j(s_j)$ to the domain of $0 \leq s_j \leq 1$, we must specify

$$\underset{s_j}{\operatorname{argmax}} U_j(s_j) = \min \left\{ \left(\frac{C + p_{jj}D}{B} \right)^{\frac{1}{B-1}}, 1 \right\}.$$

Note from Equations (2-1) and (2-2) that both utility and prescribing threshold decrease as the providers' share of their own resistance costs p_{jj} increases, where

$$\frac{\partial U_j}{\partial p_{jj}} = -Ds_j < 0$$

and

$$\frac{\partial (\operatorname{argmax}_{s_j} U_j(s_j))}{\partial p_{jj}} = \frac{D}{B(B-1)} \left(\frac{C + p_{jj}D}{B} \right)^{\frac{2-B}{B-1}} < 0,$$

since $0 < B < 1$.

We also define q_j as provider j 's perceived stewardship "moral accountability," i.e. the intrinsic weight that provider j places on the broader consequences of resistance resulting from her prescribing threshold, beyond any consequences she herself will ever incur, such that q_j increases as s_j decreases. This moral accountability means that a provider may choose to practice better stewardship than is strictly rational, acting as if she incurs some greater share $q_j > p_{jj}$ of her caused resistance costs and thus prescribe at a lower threshold. This dynamic suggests that providers' prescribing thresholds and resulting utilities also are functions of their individual sense of accountability such that if provider j assumes some accountability $0 \leq q_j \leq 1$, then her optimal prescribing strategy from Equation (2-2) becomes

$$\operatorname{argmax}_{s_j} U_j(s_j(q_j)) = \left(\frac{C + q_j D}{B} \right)^{\frac{1}{B-1}}, \quad (2-3)$$

where $s_j(q_j)$ now denotes her prescribing threshold as a function of q_j . For instance, if provider j assumes full accountability for all her caused resistance costs then $q_j = 1$ and the resulting threshold in Equation (2-2). The utility formulation for provider j then becomes

$$\begin{aligned} U_j(s_j(q_j)) &= \left(\frac{C + q_j D}{B}\right)^{\frac{B}{B-1}} - C \left(\frac{C + q_j D}{B}\right)^{\frac{1}{B-1}} - p_{jj} D \left(\frac{C + q_j D}{B}\right)^{\frac{1}{B-1}} \\ &\quad - \sum_{k \neq j} p_{jk} D \left(\frac{C + q_k D}{B}\right)^{\frac{1}{B-1}}. \end{aligned}$$

Intuitively, a rational provider will assume accountability for only the expected share of resistance costs that will eventually be incurred. To confirm, we take the derivative of this utility formulation with respect to q_j producing

$$\begin{aligned} \frac{\partial U_j}{\partial q_j} &= \frac{BD}{B(B-1)} \left(\frac{C + q_j D}{B}\right)^{\frac{1}{B-1}} - \frac{CD}{B(B-1)} \left(\frac{C + q_j D}{B}\right)^{\frac{2-B}{B-1}} - \frac{p_{jj} D^2}{B(B-1)} \left(\frac{C + q_j D}{B}\right)^{\frac{2-B}{B-1}} \\ &= \frac{D}{B(B-1)} \left[B \left(\frac{C + q_j D}{B}\right)^{\frac{1}{B-1}} - \left(\frac{C + q_j D}{B}\right)^{\frac{2-B}{B-1}} (C + p_{jj} D) \right] \\ &= \frac{D}{B(B-1)} \left(\frac{C + q_j D}{B}\right)^{\frac{1}{B-1}} \left[B - \left(\frac{C + q_j D}{B}\right)^{\frac{1-B}{B-1}} (C + p_{jj} D) \right] \\ &= \frac{D}{B(B-1)} \left(\frac{C + q_j D}{B}\right)^{\frac{1}{B-1}} \left[B - B \left(\frac{C + p_{jj} D}{C + q_j D}\right) \right] \\ &= \frac{DB}{(B-1)} \left(\frac{C + q_j D}{B}\right)^{\frac{1}{B-1}} \left[1 - \frac{C + p_{jj} D}{C + q_j D} \right]. \end{aligned}$$

Since

$$\frac{DB}{(B-1)} \left(\frac{C + q_j D}{B} \right)^{\frac{1}{B-1}} < 0$$

and

$$\left(1 - \frac{C + p_{jj} D}{C + q_j D} \right) \begin{cases} < 0 & \text{if } q_j < p_{jj} \\ = 0 & \text{if } q_j = p_{jj}, \\ > 0 & \text{if } q_j > p_{jj} \end{cases}$$

therefore,

$$\frac{\partial U_j}{\partial q_j} \begin{cases} > 0 & \text{if } q_j < p_{jj} \\ = 0 & \text{if } q_j = p_{jj}, \\ < 0 & \text{if } q_j > p_{jj} \end{cases}$$

confirming that $U_j(s_j(q_j))$ is maximized at $q_j = p_{jj}$.

Consider an alternative scenario where all providers in the network collectively agree on a uniform accountability level \bar{q} such that

$$s_j = \left(\frac{C + \bar{q} D}{B} \right)^{\frac{1}{B-1}} \quad \forall j. \quad (2-4)$$

The utility formulation for provider j then becomes

$$\begin{aligned}
U_j(s_j(\bar{q})) &= \left(\frac{C + \bar{q}D}{B}\right)^{\frac{B}{B-1}} - C \left(\frac{C + \bar{q}D}{B}\right)^{\frac{1}{B-1}} - \sum_k p_{jk} D \left(\frac{C + \bar{q}D}{B}\right)^{\frac{1}{B-1}} \\
&= (C + \bar{q}D)^{\frac{B}{B-1}} \left(\frac{1}{B}\right)^{\frac{B}{B-1}} - C(C + \bar{q}D)^{\frac{1}{B-1}} \left(\frac{1}{B}\right)^{\frac{1}{B-1}} \\
&\quad - D(C + \bar{q}D)^{\frac{1}{B-1}} \left(\frac{1}{B}\right)^{\frac{1}{B-1}} \sum_k p_{jk}.
\end{aligned}$$

Taking the derivative of the utility formulation now with respect to \bar{q} produces

$$\begin{aligned}
\frac{\partial U_j}{\partial \bar{q}} &= \frac{BD}{B-1} (C + \bar{q}D)^{\frac{1}{B-1}} \left(\frac{1}{B}\right)^{\frac{B}{B-1}} - \frac{CD}{B-1} (C + \bar{q}D)^{\frac{2-B}{B-1}} \left(\frac{1}{B}\right)^{\frac{1}{B-1}} \\
&\quad - \frac{D^2}{B-1} (C + \bar{q}D)^{\frac{2-B}{B-1}} \left(\frac{1}{B}\right)^{\frac{1}{B-1}} \sum_k p_{jk} \\
&= \frac{D(C + \bar{q}D)^{\frac{1}{B-1}}}{B-1} \left(\frac{1}{B}\right)^{\frac{1}{B-1}} \left[B \left(\frac{1}{B}\right) - C(C + \bar{q}D)^{\frac{1-B}{B-1}} - D(C + \bar{q}D)^{\frac{1-B}{B-1}} \sum_k p_{jk} \right] \\
&= \frac{D(C + \bar{q}D)^{\frac{1}{B-1}}}{B-1} \left(\frac{1}{B}\right)^{\frac{1}{B-1}} \left[1 - \frac{C}{C + \bar{q}D} - \frac{D}{C + \bar{q}D} \sum_k p_{jk} \right] \\
&= \frac{D(C + \bar{q}D)^{\frac{1}{B-1}}}{B-1} \left(\frac{1}{B}\right)^{\frac{1}{B-1}} \left[1 - \frac{C + D \sum_k p_{jk}}{C + \bar{q}D} \right].
\end{aligned}$$

Since

$$\frac{D(C + \bar{q}D)^{\frac{1}{B-1}}}{B-1} \left(\frac{1}{B}\right)^{\frac{1}{B-1}} < 0,$$

the sign of $\frac{\partial U_j}{\partial \bar{q}}$ for $0 \leq \bar{q} \leq 1$ can be determined by setting the expression

$$1 - \frac{C + D \sum_k p_{jk}}{C + \bar{q}D} \equiv 0$$

and solving for \bar{q} producing

$$\bar{q} = \sum_k p_{jk} = p_{jj} + \sum_{k \neq j} p_{jk}.$$

Since

$$\left(1 - \frac{C + D \sum_k p_{jk}}{C + \bar{q}D}\right) \begin{cases} < 0 & \text{if } \bar{q} < p_{jj} + \sum_{k \neq j} p_{jk} \\ = 0 & \text{if } \bar{q} = p_{jj} + \sum_{k \neq j} p_{jk}, \\ > 0 & \text{if } \bar{q} > p_{jj} + \sum_{k \neq j} p_{jk} \end{cases}$$

therefore,

$$\frac{\partial U_j}{\partial \bar{q}} \begin{cases} > 0 & \text{if } \bar{q} < p_{jj} + \sum_{k \neq j} p_{jk} \\ = 0 & \text{if } \bar{q} = p_{jj} + \sum_{k \neq j} p_{jk} \\ < 0 & \text{if } \bar{q} > p_{jj} + \sum_{k \neq j} p_{jk} \end{cases}$$

and provider j thus should be willing to agree to accountability $\bar{q} = p_{jj} + \sum_{k \neq j} p_{jk}$ if all providers in the network collectively agree on some uniform accountability level \bar{q} .

As a result, if a coalition of providers collectively agree to some uniform accountability level \bar{q} , then all providers are better off if $\bar{q} > p_{jj}$ than if they individually choose $q_j = p_{jj}$. Thus, if $p_{jk} > 0$ for some k , then provider j should be willing to join such a coalition for which $\bar{q} > p_{jj}$. An entity with $p_{jk} = 0 \forall k$ might be excluded from the coalition while still a contributing source of resistance. For example, agricultural use of antibiotics contributes to the spread of resistant bacteria without currently incurring any costs of treating resultant infections.

However, without sufficient oversight of such a collective accountability coalition, individual providers may be tempted to “defect” to $q_j = p_{jj}$ to the point where all providers choose $q_j = p_{jj} \forall j$ in a Nash equilibrium solution (a scenario in which no provider can increase their individual utility by unilaterally changing strategies) despite the potential gains of a coalition. Since all resistance costs produced by all N providers eventually are incurred by one or more providers in the network,

$$\sum_j p_{jk} = 1 \forall k ,$$

and thus

$$\sum_j \sum_k p_{jk} = N$$

across all providers. Under a simple arrangement in which all resistance costs produced by any provider j are evenly distributed across all providers,

$$\sum_k p_{jk} = 1 \forall j ,$$

in which case each provider should be willing to agree to collective accountability $\bar{q} = 1$ with coalition enforcement. This representation as a commons model also provides a framework for defining "rational" and "ideal" stewardship. In the Nash equilibrium provider j rationally assumes "self accountability" $q_j = p_{jj}$ (*rational* stewardship), whereas under altruistic conditions provider j assumes full accountability $q_j = 1$ for all caused costs (*ideal* stewardship).

2.3.3. Numerical Results

To illustrate with a hypothetical example, assume the benefit and cost function parameters in Equations (2-3) and (2-4) are $B = 1/3$, $C = 1/4$, and $D = 1/4$ (see Figure 2-5) and that for simplicity every provider is subject to the same share p_j of all resistance costs such that $p_{jk} = p_j \forall j, k$. The rational and ideal prescribing thresholds then are $s_* = 0.6$ and $s_* = 1$ respectively. Assuming a network of 5 hospitals each with an equal share of all resistant infections such that $p_{jk} = \frac{1}{5} \forall j, k$, Figure 2-6 illustrates the utility defined in Equation (2-1) of a single hospital H1 as a function of its prescribing threshold and assuming all other providers practice either ideal (gray line) or rational (black line) stewardship. Note in both cases that H1 increases utility by increasing its prescribing threshold from the ideal point I to the rational stewardship level II. The other hospitals all reach the same conclusion, resulting in a Nash equilibrium at point IV for which all hospitals practice rational stewardship even though all would have higher utility by collectively choosing ideal stewardship (point I).

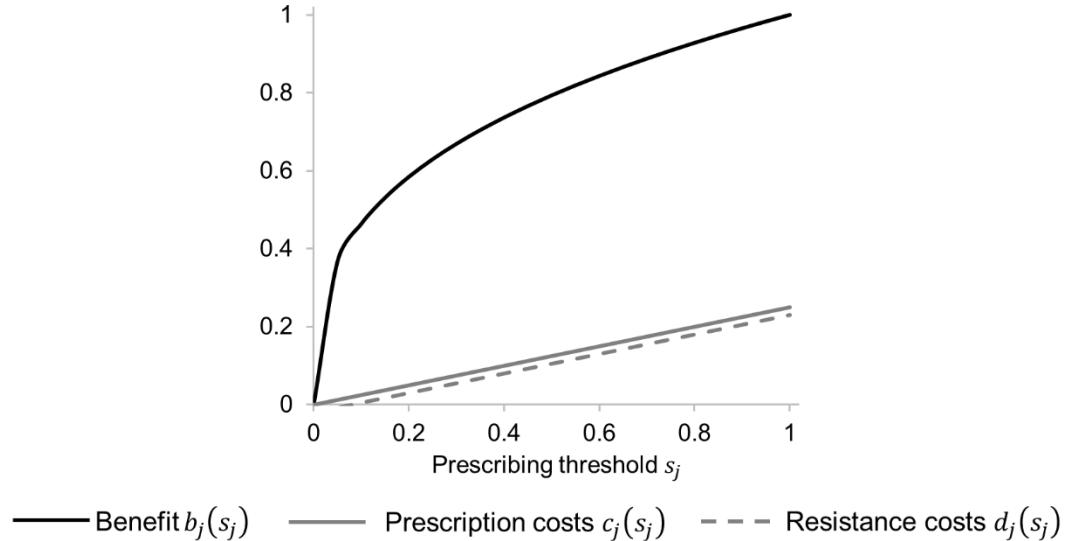


Figure 2-5. Benefits and costs for provider j as a function of prescribing threshold s_j , assuming $B = 1/3$, $C = 1/4$, $D = 1/4$

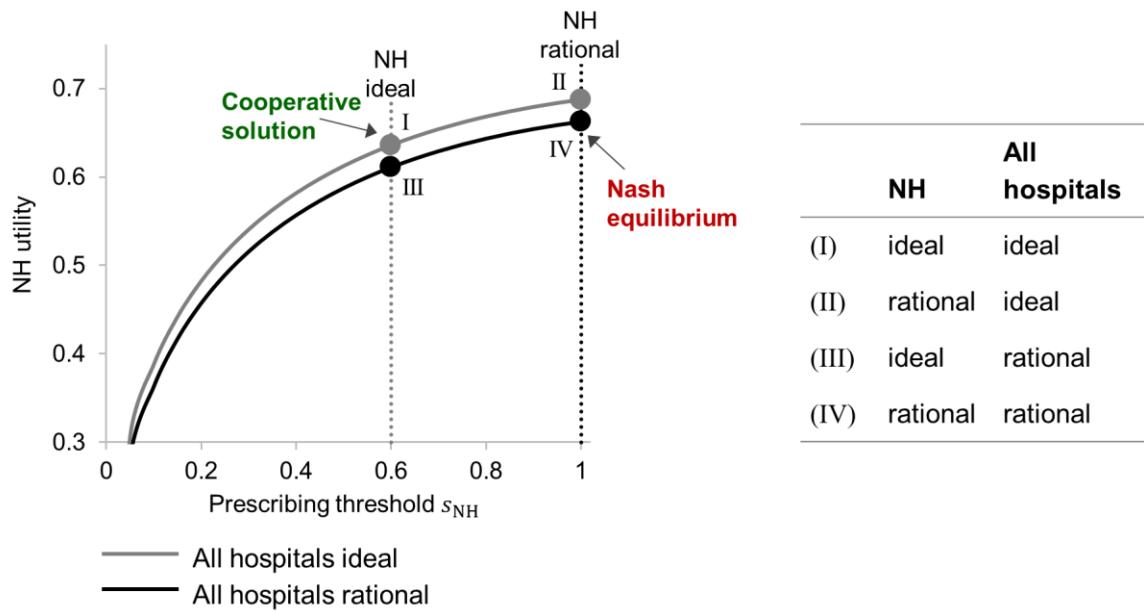
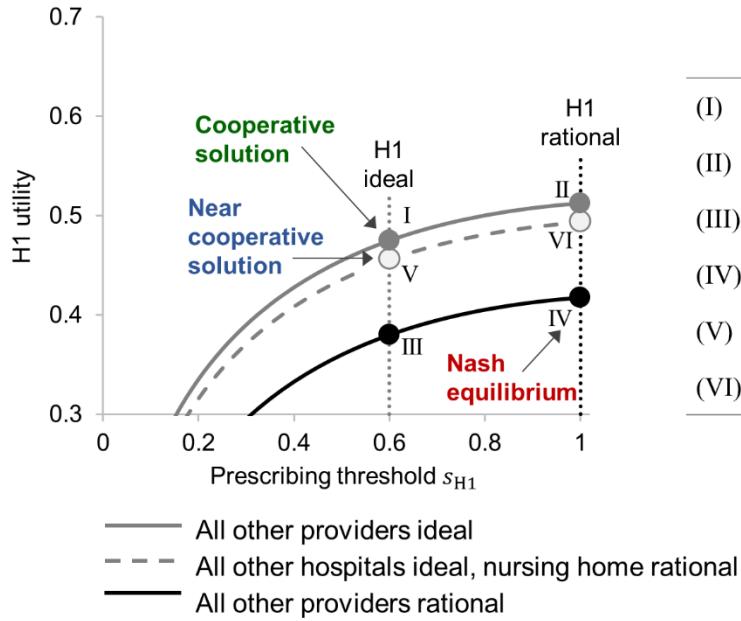


Figure 2-6. Utility for an individual hospital H1 as a function of prescribing threshold s_{H1}

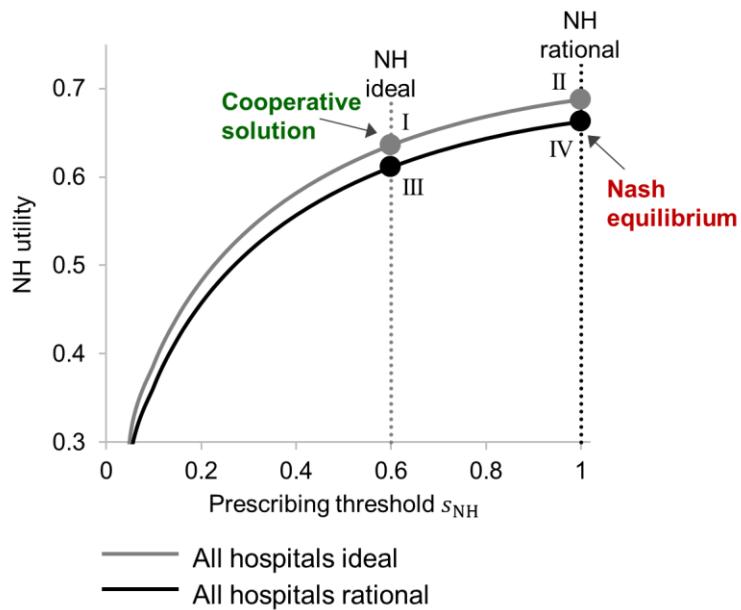
Suppose instead that the same network of 5 hospitals now also includes a nursing home (NH) with a lower share of resistant infection costs ($p_{NH,k} = 1/20 \forall k$, versus $p_{jk} = 19/100 \forall j, k$) and an agricultural source (AS) with no share of resistant infection costs ($p_{AS,k} = 0 \forall k$). With no stake in preventing resistant infections, we assume the agricultural source would practice rational stewardship in all cases in Figure 2-7, whereas the nursing home may practice ideal (gray line) or rational (dashed gray line) stewardship. As shown, although agricultural and nursing home antibiotic use reduces each hospital's overall utility, all providers again practice rational stewardship in the Nash equilibrium (IV) even though they would have higher utility at the cooperative solution (I). Note that all hospitals also are better off at the “near cooperative solution” (V), such as by forming a pact with other hospitals to practice ideal stewardship even if the nursing home practices rational stewardship. The advantage of such a pact is important because the nursing home may operate under a different incentive structure.

In contrast, given a lower share of resistance costs the nursing home experiences higher utility at the Nash equilibrium (IV) than the cooperative solution (I), with no incentive to practice ideal stewardship (see Figure 2-8). Also note the “nursing home” in this example could represent any other type of non-hospital healthcare facility that incurs a low but nonzero share of resistant infection costs. The practical importance of these results is that, although a moral appeal may convince some providers to improve stewardship beyond p_{jj} , there is no existing incentive to encourage cooperating on ideal stewardship. To advance the ideals of the National Action Plan, therefore we must consider how to design policies that help maintain collective provider compliance to ideal stewardship.



	H1	NH	All other hospitals
(I)	ideal	ideal	ideal
(II)	rational	ideal	ideal
(III)	ideal	rational	rational
(IV)	rational	rational	rational
(V)	ideal	rational	ideal
(VI)	rational	ideal	ideal

Figure 2-7. Utility for hospital H1 as a function of prescribing threshold s_{H1} with the addition of a nursing home (NH) and agricultural source (AS)



	NH	All hospitals
(I)	ideal	ideal
(II)	rational	ideal
(III)	ideal	rational
(IV)	rational	rational

Figure 2-8. Utility for nursing home NH as a function of prescribing threshold s_{NH}

2.4. Policy Implications

2.4.1. Forming Cooperative Institutions

While the National Action Plan indicates that healthcare organizations and states prescribing antibiotics at above average rates will be targeted for federal intervention, it leaves room for interpretation about how to best manage statewide stewardship programs. Ostrom's design principles (summarized in Table 2-2) provide a framework for multiple entities to reach sustainable agreements to prevent commons tragedies in a variety of contexts and thus may be instructive here to help local providers create effective cooperative arrangements.

As an example, consider Ostrom's case study of three open-access groundwater basins in Southern California in the mid-20th century. Many institutions with natural geographic claim to the basins (32 in the smallest basin, over 500 in the largest basin) were able to pump high-quality water at a cheaper rate than importing, and the basins' storage capacity reduced the need for water tanks. Over-extraction was the dominant strategy until the water pumpers organized and introduced legislation to reduce the water extracted. Table 2-3 outlines the application of Ostrom's framework to California groundwater basin management, while relative to antibiotic use and to give some illustration for further research, Table 2-4 suggests how this framework might be applied to statewide program design.

Table 2-2. Ostrom's design principles for managing common-pool resources [74]

Design principle	Description
<i>Clearly defined boundaries</i>	Those who have rights to use the resource must be clearly defined.
<i>Congruence between rules and local condition</i>	Rules restricting resource use are related to local conditions.
<i>Collective-choice arrangements</i>	Those affected by the operational rules can participate in modifying these rules.
<i>Monitoring</i>	Monitors who audit resource use are accountable to the users.
<i>Graduated sanctions</i>	Violation of operational rules is subject to graduated sanctions.
<i>Conflict-resolution mechanisms</i>	There are accessible, low-cost local arenas to resolve conflicts among resource users.
<i>Minimal recognition of rights to organize</i>	The rights of the institution are not challenged by external governmental authorities.
<i>Nested enterprises</i>	Institutions that are part of a larger system are organized in multiple layers of nested enterprises.

Table 2-3. Illustration of Ostrom's design principles for California basin case study

Design principle	Application for groundwater basins
<i>Clearly defined boundaries</i>	Water rights were allocated to define who could withdraw water from the basin and how much water could be withdrawn. These water rights could be sold.
<i>Congruence between rules and local condition</i>	The water restrictions varied according to the geographic situation of the basin and the number of water pumbers who accessed the basin.
<i>Collective-choice arrangements</i>	The pumbers created voluntary water associations to organize communication between pumbers to draft the initial legislation proposal. These associations continued to hold regular meetings to discuss proposed changes in regulating the basins.
<i>Monitoring</i>	Each pumper reports total groundwater extractions every year, monitored by the neutral “watermaster” service. The association pays for most of the watermaster service budget and can petition the court to appoint a different watermaster if they are not satisfied.
<i>Graduated sanctions</i>	The annual report pays special attention to reporting the recent activities of a pumper suspected of intentional overuse. Continued noncompliance invites formal legal sanctions. Legal action is taken against new pumbers who attempt to extract water without purchasing water rights.
<i>Conflict-resolution mechanisms</i>	Regular meetings of the water associations allow for conflict-resolution mechanisms between pumbers. The continuing jurisdiction of the court supports conflict resolution through litigation if necessary.
<i>Minimal recognition of rights to organize</i>	The California courts upheld the structure of the initial proposals by the water associations and continue to recognize the pumbers' right to organize.
<i>Nested enterprises</i>	Water associations may form a district with the power to tax to raise revenue and take action to replenish a groundwater basin. The associations and districts comprise Southern California's effort to manage the groundwater basin water supply.

Table 2-4. Illustration of how Ostrom's design principles might be applied to a statewide antibiotic stewardship program

Design principle	Application to statewide program
<i>Clearly defined boundaries</i>	Define and disseminate clear guidelines for appropriate use of antibiotics. Restrict inappropriate use of antibiotics when possible.
<i>Congruence between rules and local condition</i>	Tailor mitigation strategy recommendations to reflect local prevalence trends of resistant bacteria.
<i>Collective-choice arrangements</i>	Report status update on local antibiotic use and bacterial surveillance at regular meetings with established means for members to communicate feedback.
<i>Monitoring</i>	Establish a “drugmaster” service: an individual or small team responsible for verifying and reporting local antibiotic use and bacterial surveillance.
<i>Graduated sanctions</i>	Unclear if explicit sanctions are appropriate or enforceable with a statewide program. Transparency in reporting antibiotic use may be sufficient to promote accountability.
<i>Conflict-resolution mechanisms</i>	Address conflict with member organizations at regular meetings. Continued noncompliance with preferred prescription rates may require intervention from the federal program.
<i>Minimal recognition of rights to organize</i>	The federal program indicates it will respect the authority of statewide programs if antibiotic use is at or below the average national rate.
<i>Nested enterprises</i>	The statewide programs are nested into the larger national program.

2.4.2. Realigning Incentives

In any case, if the statewide programs do not meet the NAP milestones by 2020 and fail to reduce antibiotic use with cooperative institutions, the federal government may find it necessary to intervene. In this context, a tax on antibiotic purchases (often called a “Pigovian tax” in economic language, a tax on some activity that produces negative externalities) could be an effective way to reduce antibiotic use by reflecting the costs of resistance in the direct costs to the provider and patient, as also suggested by Coast et al. [135, 136], similar to a carbon tax. Operationally and mathematically, suppose there is some s^* that represents optimal antibiotic use from a societal perspective. The cost parameters C and D in Equation (2-1) may be altered to make s^* the dominant strategy, such that

$$s^* = \operatorname{argmax}_{s_j} U_j .$$

Suppose that s^* is a function of some q^* at the present levels of B , C , and D , such that

$$s^* = \left(\frac{C + q^* D}{B} \right)^{\frac{1}{B-1}} . \quad (2-5)$$

Letting C^* and D^* represent the levels of C and D that will incentivize provider j to choose s^* , substituting s^* for s_j while holding other inputs constant in Equation (2-5) produces

$$C^* = C + D(q^* - p_{jj})$$

and

$$D^* = \frac{q^* D}{p_{jj}} .$$

Using these results, Figure 2-9 compares the utility of hospital H1 as a function of its prescribing threshold after a calculated antibiotic tax, assuming $q^* = 1$ and $s^* = 0.6$, to alternatives from the pre-tax incentive structure (see Figure 2-6). Now H1 maximizes utility at point VII, where all hospitals choose the same prescribing threshold that previously was identified as ideal stewardship. The tax effectively moves the Nash equilibrium from point IV to VII so that now ideal stewardship (the desired state) becomes the utility-maximizing strategy for all providers. Importantly, note that the tax sacrifices provider utility, however, meaning that the hospitals would be better off instead prescribing at the pre-tax threshold level (I) to avoid a tax which forces them to move to this same prescribing level (VII) but with lower utility. Thus the credible threat of an antibiotic tax, if statewide programs do not meet the NAP milestones by 2020, may motivate providers to find cooperative solutions in order to avoid this consequence.

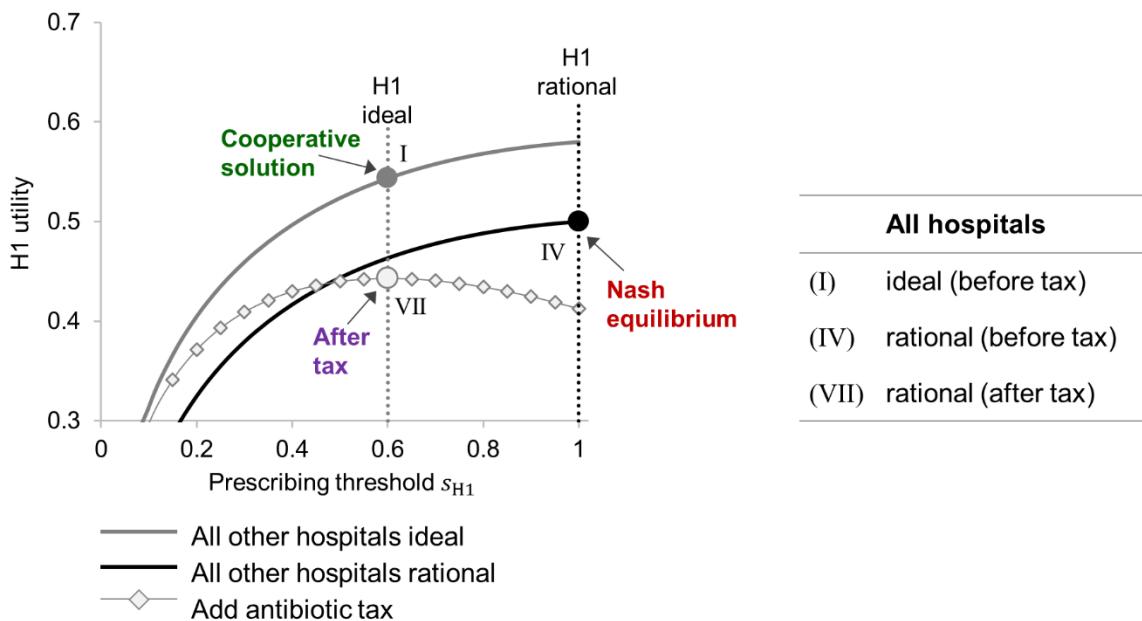


Figure 2-9. Impact of an antibiotic use tax on utility for hospital H1 as a function of prescribing threshold s_{H1}

As an alternate external mechanism, the government could penalize providers or hospitals with high rates of resistant infections. The Centers for Medicare and Medicaid Services already has established policies to levy financial penalties for certain resistant infections such as Methicillin-resistant *Staphylococcus aureus* infections and *Clostridium difficile* infections. Figure 2-10 therefore compares the utility of hospital H1 after a calculated penalty for resistant infections, assuming $q^* = 1$ and $s^* = 0.6$, to the same alternatives from the pre-tax incentive structure. Although this penalty also moves the Nash equilibrium from (IV) to (VIII), so that ideal stewardship again becomes the utility-maximizing strategy for all providers, it is a less desirable solution because it sacrifices more provider utility to achieve ideal stewardship. This has practical insight since a tax on antibiotic use therefore appears preferable over current practices to impose penalties on resistant infections.

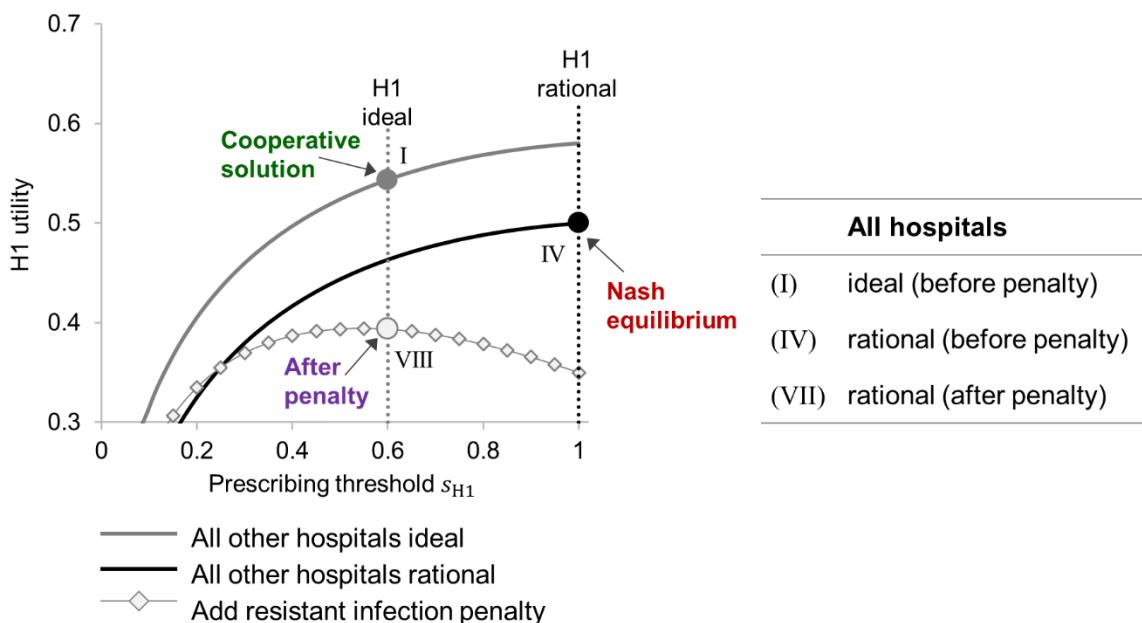


Figure 2-10. Impact of a resistant infection penalty on utility for hospital H1 as a function of prescribing threshold s_{H1}

2.5. Discussion

After decades of rational yet unsustainable antibiotic overuse, the *National Action Plan for Combating Antibiotic-Resistant Bacteria* set expectations for antibiotic stewardship and promised federal resources to help providers achieve these. For statewide stewardship programs to succeed, each healthcare organization must comply with best practice guidelines for prescribing, monitor antibiotic use, conduct surveillance for antibiotic-resistant bacteria, and report findings with transparency. Within any given region, participating healthcare organizations should encourage others to join their statewide program, since avoiding a commons tragedy is sensitive to even a modest minority of rational defectors. Given this challenge, Ostrom's principles for designing effective community management programs may help providers create sustainable cooperative arrangements without the need for less effective outside intervention. To motivate commitment to statewide programs, however, the credible threat of the federal government imposing a tax on antibiotic purchases or penalties for infection rates may still be effective.

The utility model developed in this chapter helps illustrate these policies and conclusions and provide additional insight to effective strategies and incentives for promoting better collective stewardship. While an antibiotic tax appears to be effective to reduce overuse and non-compliance to evidence-based guidelines, it results in lower provider utility than a collective agreement to follow these same prescribing practices. Quantifying the inputs to the benefit-cost calculation of the appropriate tax level also may be difficult. Such a tax additionally may not sufficiently influence physicians who are not explicitly

conscious of purchasing costs. By whatever method, care must be taken that heightened focus on prescribing rates does not create a perverse underuse incentive in cases for which antibiotics are indicated.

A few limitations of the analyses in this chapter include the underlying model being time-static, whereas a time-dynamic model could account for the fluctuation prescribing benefits over time as resistance changes, which might result in a different Nash equilibrium. An alternate approach than utility maximization also might be more persuasive to healthcare providers, such as one that more directly models resistant infections as a function of prescribing rates. Finally, while this chapter focuses on the role of providers, comprehensive efforts also should include strategies to reduce agricultural overuse and to improve patient compliance to antibiotic therapy.

Chapter 3. Volunteer's Dilemmas in Care Coordination to Prevent Readmissions

3.1. Introduction

The volunteer's dilemma is a type of social dilemma for which any individual can act to achieve an outcome that benefits a larger group, yet if no one acts the entire group disbenefits. Each individual thus must decide whether to incur the cost of acting or hope someone else in the group volunteers. As an example, Darley and Latané [137] noted a tragic case in which a woman was stabbed to death in the middle of a public street while at least 38 bystanders witnessed the attack from nearby apartments. Although presumably every bystander preferred the woman be rescued, since each was aware of the others no bystander incurred the inconvenience of calling the police.

Stavert and Lott [138] noted this “bystander effect” associated with the volunteer's dilemma also exists in the healthcare industry, where multiple providers are responsible for the health of each patient in a broader care system. An analysis of Medicare claims from 2000-2002 for 1.8 million beneficiaries revealed patients visited a median of 2 primary care physicians and 5 specialists working in 4 different practices [139]. The authors thus recommended that development of financial incentives should incorporate strategies to ensure care provision across such a large number of providers.

We explore the existence of volunteer dilemmas in accountable care organizations (ACOs) in which providers share responsibility for a patient population. The Centers for Medicare and Medicaid Services (CMS) [140] describe ACOs as “groups of doctors, hospitals, and other healthcare providers, who come together voluntarily to give coordinated high quality care to their Medicare patients.” ACOs may adopt a mixture of reimbursement methods, so providers in an ACO face a complex dynamic of financial reimbursements, opportunity cost, and moral incentives when choosing how and when to provide care. Care coordination failures can be viewed in this economic context as suboptimal equilibria and examined for ways to design structures with appropriate incentives to provide more coordinated care. As an example, CMS provides financial incentives through a shared savings program based on how well an ACO performs in specific quality measures, one being a risk-adjusted 30-day readmission rate. After a patient is discharged from a hospital, each entity involved in the patient’s care may act with some care intervention to reduce the probability of readmission—each is better off if another acts first, hence a volunteer’s dilemma.

After a summary of recent research on care coordination and post-discharge care to prevent readmissions, we develop the volunteer’s dilemma model, identify three mechanisms to ensure appropriate action and prevent failures in care coordination, and illustrate these with an example. Next, we examine the mixed strategy equilibrium for the volunteer’s timing. Finally, we discuss the implications of these results, insights into current practice and trends, and potential extensions.

3.2. Literature Review

3.2.1. Care Coordination and Post-Discharge Care

The Patient Protection and Affordable Care Act (PPACA) promotes care coordinated by a team of providers through a patient-centered medical home model [141]. Among its many provisions, PPACA devoted \$500 million to the Community-based Care Transitions Program to test ways to improve care transitions between hospitals and other settings that could reduce readmissions for high-risk Medicare beneficiaries. CMS also established financial penalties for high readmission rates after finding nearly 20% of Medicare beneficiaries were readmitted within 30 days after discharged from hospitals [142].

Consensus on effective interventions to prevent readmission however are unclear and inconsistent. For the Medicare Coordinated Care Demonstration, CMS selected 15 sites (5 commercial disease management companies, 3 community hospitals, 3 academic medical centers, 1 integrated delivery system, 1 hospice, 1 long-term care facility, and 1 retirement community) to test a variety of readmission interventions from 2002-2005. Only one intervention was associated with a significant reduction in hospitalizations and no interventions generated net savings [143]. The reviewers instead recommended two proven transitional care models [144-146] that demonstrated a reduction in readmissions as a potentially rewarding area for generating savings when considering the medical home model.

In a systematic review of randomized clinical trials of transitional care interventions targeting chronically ill adults, Naylor et al. [147] defined transitional care as a “broad range of time-limited services designed to ensure healthcare continuity, avoid preventable poor outcomes among at-risk populations, and promote the safe and timely transfer of patients from one level of care to another or from one type of setting to another.” Eight of the 21 studies reported a statistically significant positive effect on the all-cause readmission rate. Successful interventions included discharge management plus follow-up [145-150], coaching [144, 151], and telehealth [152].

A second systematic review of hospital-initiated care transition interventions with both pre- and post-discharge components found that 10 of 20 interventions with a dedicated transition provider yielded a statistically significant reduction in readmissions or ED visits, while 2 of 10 interventions with no dedicated transition provider yielded a statistically significant reduction in readmissions or ED visits [153]. A Cochrane review of randomized control trials comparing individually tailored discharge plans to routine discharge care found that discharge planning resulted in a statistically significant reduction in readmission rates for elderly patients with a medical condition [154]. In terms of cost-effectiveness, Rennke et al. [153] and Donald et al. [155] called for better reporting of the costs of transitional care interventions and stronger economic analysis to evaluate transitional care interventions.

3.2.2. Volunteer's Dilemma

Figure 3-1 illustrates Diekmann's formulation [156] for the basic N -player volunteer's dilemma, where c is the cost to produce the collective good and b is the benefit to each player if the collective good is produced. Each player can guarantee a payoff $b - c > 0$ by volunteering. If a player does not volunteer, the payoff is b if another player volunteers and 0 if no one volunteers.

		Number of players who volunteer				
		0	1	2	...	N
Volunteer	0	$b - c$	$b - c$	$b - c$...	$b - c$
	Not volunteer	0	b	b	...	b

Figure 3-1. Payoff table for one player in the volunteer's dilemma ($N \geq 2$, $b - c > 0$)

Schelling's "mattress problem" [157] is an example of a volunteer's dilemma where $b - c < 0$ that informs this work. In a repeated game, the assignment of volunteer responsibility can rotate between players. Diekmann notes two equilibrium strategies. In the asymmetric equilibrium, one player volunteers and $(N - 1)$ players defect. In a repeated vocal game, the assignment of volunteer responsibility can rotate between players. In the mixed strategy equilibrium, player j volunteers with probability q_j ,

$$q_j = \left[\frac{c_j}{b_j} \right]^{\frac{1}{N-1}}.$$

While it is expected that the collective good is always produced in the asymmetric equilibrium, in the mixed strategy equilibrium the probability Q that the collective good is produced is a decreasing function of N . In the symmetric case where $c_j = c \forall j$ and $b_j = b \forall j$, the probability that the collective good is produced is

$$Q = 1 - \left[\frac{c}{b} \right]^{\frac{N}{N-1}}.$$

It is troubling that both theoretical formulation [156, 158-159] and experimental evidence [160] show that the probability of failure to produce the collective good increases with group size. Diekmann and Weesie independently researched variations on the traditional volunteer's dilemma in which timing is a factor [156, 161], there exists incomplete or imperfect information [158], the cost of producing the good can be shared [159], and payoffs are asymmetric [160, 161].

3.3. Mechanisms for the Asymmetric Equilibrium

3.3.1. Model Formulation

We apply Diekmann's model to a network of N providers responsible for M patients who are candidates for a designated intervention to prevent readmission. Examples might be a post-discharge phone call, a visit to the patient's home, or a follow-up appointment at a primary care facility to confirm a patient is following post-discharge instructions and evaluate the progression of the patient's health status. We suppose an ACO comprised of independent physicians default to the asymmetric equilibrium solution to the volunteer's dilemma: one provider volunteers, the remaining $(N - 1)$ players do not volunteer, and the responsibility to volunteer rotates between providers. In this context, suppose each

provider is the primary physician for a subset of the ACO patient population. When an intervention is indicated for a patient, the general responsibility to act typically lies with the patient's primary physician or care team. Figure 3-2 illustrates how 3 interventions may be completed by 3 providers, wherein all interventions are conducted and the total costs are shared equally by all providers. This asymmetric equilibrium is a case of a Nash equilibrium since no provider has anything to gain by changing strategy.

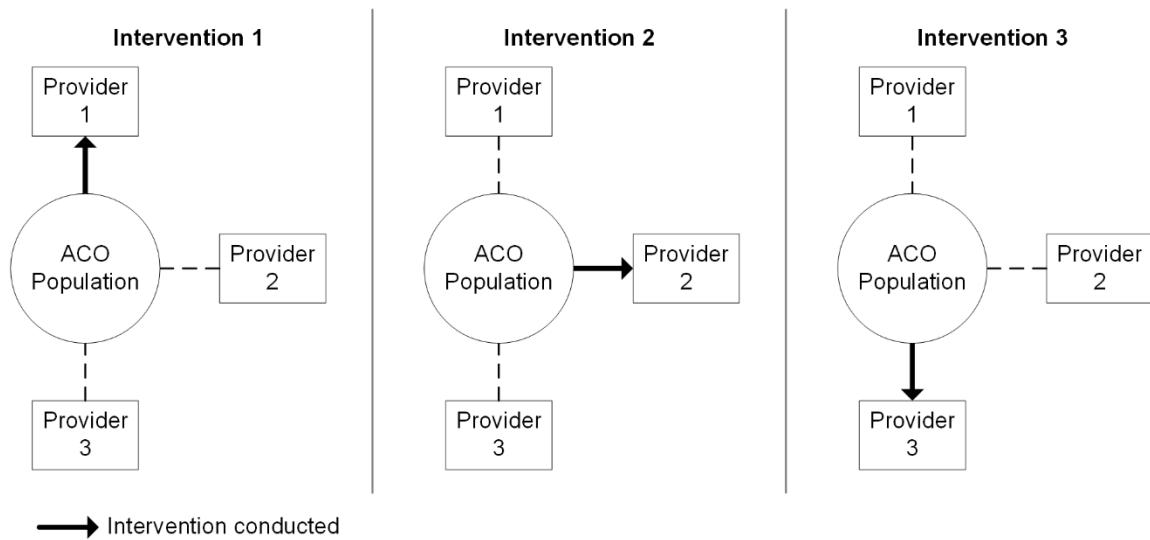


Figure 3-2. Example of 3 intervention, 3 providers scenario in which all interventions are conducted

Given uncertainty about which readmissions are avoidable [162], providers may disagree about an intervention's effectiveness to prevent readmission and thus each may weigh its cost-benefit differently. Using the notation in Table 3-1, we assume the benefit of preventing a readmission by provider j for patient i is greater than the cost of the intervention for all providers and patients ($b_{ij} - c_{ij} > 0 \forall i, j$), where $s_{ij} = 1$ indicates provider j intervenes for patient i and ϕ_{ij} is provider j 's belief that the intervention will

be effective for patient i . Rationally, if provider j estimates the expected benefit of intervening is less than the cost of conducting the intervention ($b_{ij}\phi_{ij} - c_{ij} < 0$), provider j is unlikely to intervene.

Table 3-1. Notation for volunteer's dilemma model to describe ACO interventions to prevent readmission

Variable	Definition
ϕ_{ij}	Provider j estimate of probability of favorable outcome with intervention for patient i
$(1 - P_{ij})$	Probability that another provider will volunteer to intervene with patient i if provider j does not volunteer
b_{ij}	Benefit to provider j if patient i is not admitted
c_{ij}	Cost to provider j to intervene for patient i
s_{ij}	Binary variable that equals 1 if provider j intervenes for patient i

Summing across all $k = 1, \dots, N$ providers, $\sum_k s_{ik} \in \{0,1\} \forall i$ because at most one volunteer per patient is permitted. Additionally, provider j estimates that patient i will not be readmitted with probability $\Theta_{ij}^{(1)}$ if an intervention is conducted and $\Theta_{ij}^{(0)}$ if no intervention is conducted, where $\Theta_{ij}^{(1)} \geq \Theta_{ij}^{(0)}$ is assumed, and thus

$$\phi_{ij} \left(\sum_k s_{ik} \right) = \begin{cases} \Theta_{ij}^{(1)} & \text{if } \sum_k s_{ik} = 1 \\ \Theta_{ij}^{(0)} & \text{if } \sum_k s_{ik} = 0 \end{cases}.$$

The utility of provider j when choosing to either volunteer for patient i ($s_{ij} = 1$) or abstain ($s_{ij} = 0$) from intervening given actions of all other providers is

$$U_{ij}(s_{ij}) = b_{ij}\phi_{ij} \left(\sum_k s_{ik} \right) - c_{ij}s_{ij}.$$

Which strategy other providers will choose is uncertain, so the expected value of this utility for provider j is

$$E[U_{ij}(s_{ij})] = b_{ij}E\left[\phi_{ij} \left(\sum_k s_{ik} \right)\right] - c_{ij}s_{ij}.$$

Let $(1 - P_{ij})$ denote the probability that another provider will volunteer to intervene with patient i if provider j does not. the expected utilities of volunteering ($s_{ij} = 1$) and abstaining ($s_{ij} = 0$) are

$$E[U_{ij}(s_{ij} = 1)] = b_{ij}\Theta_{ij}^{(1)} - c_{ij}$$

and

$$E[U_{ij}(s_{ij} = 0)] = b_{ij}(1 - P_{ij})\Theta_{ij}^{(1)} + b_{ij}P_{ij}\Theta_{ij}^{(0)},$$

respectively. Conditions under which provider j will choose to act and to not act occur when the difference between the above is positive,

$$\begin{aligned} E[U_{ij}(s_{ij} = 1)] - E[U_{ij}(s_{ij} = 0)] &= b_{ij}\Theta_{ij}^{(1)} - c_{ij} - b_{ij}(1 - P_{ij})\Theta_{ij}^{(1)} - b_{ij}P_{ij}\Theta_{ij}^{(0)} \\ &= -c_i + b_{ij}P_{ij}\Theta_{ij}^{(1)} - b_{ij}P_{ij}\Theta_{ij}^{(0)} \\ &= b_{ij}(\Theta_{ij}^{(1)} - \Theta_{ij}^{(0)})P_{ij} - c_{ij}. \end{aligned}$$

Provider j then chooses to act when

$$b_{ij}(\Theta_{ij}^{(1)} - \Theta_{ij}^{(0)})P_{ij} - c_{ij} > 0$$

and to not act when

$$b_{ij}(\Theta_{ij}^{(1)} - \Theta_{ij}^{(0)})P_{ij} - c_{ij} < 0.$$

Two necessary conditions for volunteering can be derived from this formulation. Namely provider j will abstain if it is believed either that (a) another provider is sufficiently likely to volunteer or (b) the marginal effect of an intervention on the probability of a favorable outcome is sufficiently low. The first condition occurs when

$$s_{ij} = \begin{cases} 1 & \text{if } 1 - P_{ij} < 1 - \frac{c_{ij}}{b_{ij}(\Theta_{ij}^{(1)} - \Theta_{ij}^{(0)})}, \\ 0 & \text{if } 1 - P_{ij} > 1 - \frac{c_{ij}}{b_{ij}(\Theta_{ij}^{(1)} - \Theta_{ij}^{(0)})} \end{cases}$$

and the second condition occurs when

$$s_{ij} = \begin{cases} 1 & \text{if } (\Theta_{ij}^{(1)} - \Theta_{ij}^{(0)}) > \frac{c_{ij}}{b_{ij}P_{ij}}, \\ 0 & \text{if } (\Theta_{ij}^{(1)} - \Theta_{ij}^{(0)}) < \frac{c_{ij}}{b_{ij}P_{ij}} \end{cases}$$

In an asymmetric equilibrium $(1 - P_{ij}) = 0$ for all patients whose care is supervised by provider j , so the first condition is always satisfied.

To examine the second condition, let Ψ_j represent the set of patients for whom provider j is responsible. Assuming provider j chooses to act ($s_{ij} = 1$) for all $i \in \Psi_j$ and not to act ($s_{ij} = 0$) for all $i \notin \Psi_j$, the total utility for provider j across all patients, U_{ij}^* , is

$$U_{ij}^* = \sum_i U_{ij} = \sum_i b_{ij}\Theta_{ij}^{(1)} - \sum_{i \in \Psi_j} c_{ij}s_{ij}.$$

To be sufficiently motivated to volunteer, provider j must believe

$$\Theta_{ij}^{(1)} - \Theta_{ij}^{(0)} > \frac{c_{ij}}{b_{ij}} \quad \forall i, j.$$

Suppose instead that some provider X is “pessimistic” and believes

$$\Theta_{iX}^{(1)} - \Theta_{iX}^{(0)} < \frac{c_{iX}}{b_{iX}} \quad \forall i,$$

such that provider X abstains from intervening for patients $i \in \Psi_X$. If all other providers remain “optimistic,” provider X still benefits from interventions conducted by the other providers for patients $i \notin \Psi_X$ and the total utility to provider X across all ACO patients is

$$\sum_i U_{iX} = \sum_{i \notin \Psi_X} b_{iX}\Theta_{iX}^{(1)} + \sum_{i \in \Psi_X} b_{iX}\Theta_{iX}^{(0)} > U_{iX}^*.$$

In contrast, the total utility across all patients for an “optimistic” provider Y decreases because provider X abstains to

$$\sum_i U_{iY} = \sum_{i \notin \Psi_X} b_{iY}\Theta_{iY}^{(1)} + \sum_{i \in \Psi_X} b_{iY}\Theta_{iY}^{(0)} - \sum_{i \in \Psi_Y} c_{iY}s_{iY} < U_{iY}^*.$$

Thus a pessimistic provider rationally may not conduct interventions but thereby produce a suboptimal group outcome for the other providers.

Figure 3-3 illustrates how this care breakdown can occur for a 3 intervention, 3 provider case where optimistic providers (Provider 1 and Provider 2) intervene and a pessimistic provider (Provider 3) does not intervene.

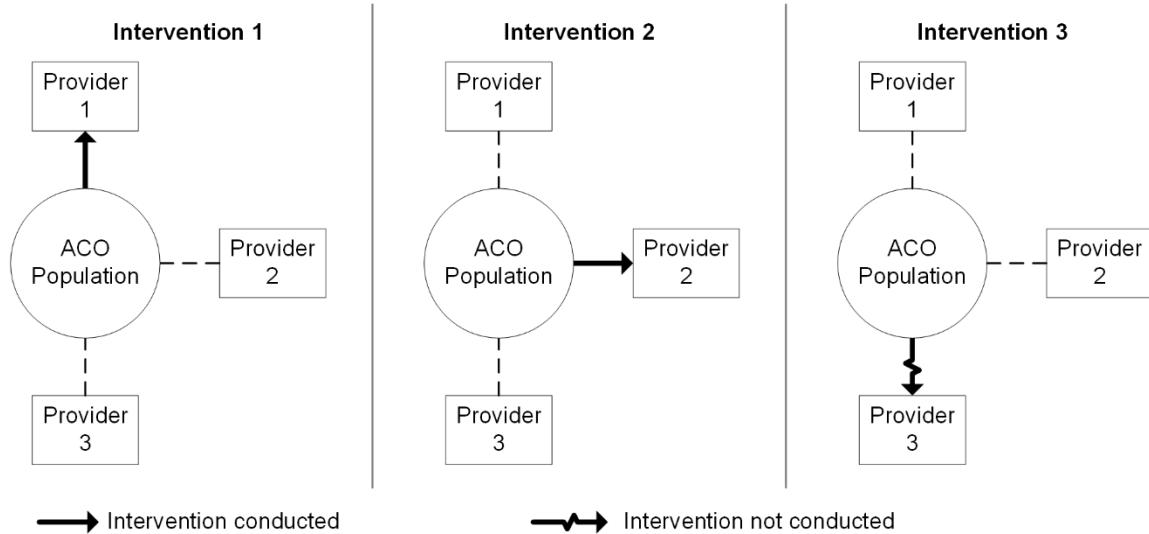


Figure 3-3. Example of optimistic and pessimistic providers—3 intervention, 3 providers scenario in which only 2 of 3 interventions are conducted

3.3.2. Analytical Results

In these types of scenarios, often mechanisms can be designed to prevent an undesirable outcome. Here we propose three types of strategies to mitigate the effect of pessimistic providers and ensure all desired interventions are conducted:

- Reassign:* Reassign interventions from pessimistic providers to more optimistic providers,
- Outsource:* Outsource interventions to a third party or vendor outside the ACO,
- Penalty:* Levy a penalty to incentivize pessimistic providers to conduct indicated interventions.

a. Reassign Interventions to Optimistic Providers

The general concept here is to reassign to optimistic providers more likely to intervene any interventions that pessimistic providers likely would not conduct. Mathematically, suppose providers $[1 \dots k]$ are optimistic such that

$$\Theta_{ij}^{(1)} - \Theta_{ij}^{(0)} \geq \frac{c_{ij}}{b_{ij}} \quad \forall i, j \in [1 \dots k],$$

and providers $[k + 1 \dots N]$ are pessimistic such that

$$\Theta_{ij}^{(1)} - \Theta_{ij}^{(0)} < \frac{c_{ij}}{b_{ij}} \quad \forall i, j \in [k + 1 \dots N].$$

Responsibility for intervening for the patients in $\bigcup_{j=k+1}^N \Psi_j$ could be redistributed to providers $[1 \dots k]$ by any method agreed upon by all providers. This of course would create disparity, dividing providers into one group that bears the full cost of interventions and another group of free riders. To reduce this disparity, the pessimistic providers could be charged or pay a fee to the providers who assume responsibility for the additional interventions. Let f_{ij} be the fee for provider j to transfer intervention responsibility for patient i . Rationally, provider j should be willing to agree to a fee less than the expected marginal benefit of intervening, or

$$f_{ij} \leq b_{ij} \left(\Theta_{ij}^{(1)} - \Theta_{ij}^{(0)} \right).$$

The total utility for a pessimistic provider $j \in [k + 1 \dots N]$ then becomes

$$\sum_i U_{ij} = \sum_i b_{ij} \Theta_{ij}^{(1)} - \sum_{i \in \Psi_j} f_{ij} > U_{ij}^*.$$

The distribution of fees likely would depend on the redistribution of interventions—one simple solution would split the total fees $\sum_i \sum_{j \in [k+1..N]} f_{ij}$ and the costs of redistributed interventions evenly among the optimistic providers $[1..k]$. If we assume the intervention cost c_i for patient i is the same for all providers (i.e., $c_{ij} = c_i \forall j$), the utility for an optimistic provider $j \in [1..k]$ is

$$\sum_i U_{ij} = \sum_i b_{ij} \Theta_{ij}^{(1)} + \left(\frac{1}{k}\right) \left[\sum_i \sum_{j \in [k+1..N]} f_{ij} - \sum_{i \in U_{j=k+1}^N} c_i \right].$$

This solution likely results in lower utility than U_{ij}^* for provider j , but this outcome is preferable to the scenario where patients with pessimistic primary providers do not receive interventions. Note that this approach could create an incentive for naturally optimistic providers to “signal” pessimism if it now is more advantageous to reassign interventions. A provider’s capacity to conduct additional interventions also could limit redistribution options. Finally, a similar outcome to the “volunteer’s timing dilemma,” in which the party with the highest benefit-cost ratio volunteers first [161], is possible here in which all interventions are conducted by the most optimistic provider.

b. Outsource Interventions to Outside Vendor

A second similar approach could reassign to a third party any interventions that pessimistic providers likely would not conduct. Suppose there is a vendor outside a health network who will intervene for a fee f per intervention. If f is sufficiently low, all providers should be willing to agree to outsource interventions to the vendor. We start with the goal to find the maximum value of f that all providers would agree to pay.

Similar to above, provider j is willing to agree to a fee less than the expected marginal benefit of intervening, or

$$f_{ij} \leq b_{ij}(\Theta_{ij}^{(1)} - \Theta_{ij}^{(0)}).$$

Let f_j be the average of $f_{ij} \forall i \in \Psi_j$ such that

$$f_j = \left(\frac{1}{|\Psi_j|} \right) \sum_{i \in \Psi_j} b_{ij}(\Theta_{ij}^{(1)} - \Theta_{ij}^{(0)}),$$

where $|\Psi_j|$ is the count of patients supervised by provider j . The maximum f that all providers would agree to pay then is bounded by the most pessimistic provider with the lowest f_j , or

$$f = \min \bigcup_j f_j.$$

Two factors could keep the vendor price sufficiently low relative to the most pessimistic provider's willingness to pay:

- *Specialization*: Opportunity costs may be a factor for busy providers, as conducting interventions pulls focus away from other valuable or profitable services, whereas these may be lower for a vendor specializing in post-discharge follow-up, and
- *Economies of scale*: A vendor also may have a lower intervention cost if this activity is a primary focus of their enterprise.

If $\min \bigcup_j f_j$ is too low to be viable for vendors, paying a higher fee might be possible by leveraging more optimistic providers' willingness to pay a higher fee, although this creates an undesirable disparity in the fees each provider incurs.

c. Levy a Penalty to Incentivize Pessimistic Providers

A third possibility is to introduce a penalty so that it is no longer rational for pessimistic providers not to intervene. Although in practice these incentives likely would be bundled with multiple performance objectives, for simplicity we consider a single type of intervention. Let g be the penalty levied if an intervention is not conducted. Provider j rationally will conduct the intervention if

$$g \geq b_{ij}(\Theta_{ij}^{(0)} - \Theta_{ij}^{(1)}) + c_{ij}.$$

It follows that $g = \max \cup_{i,j} [b_{ij}(\Theta_{ij}^{(0)} - \Theta_{ij}^{(1)}) + c_{ij}]$ in order to sufficiently motivate all providers to conduct all indicated interventions. Such an incentive structure also could be implemented as a reward for conducting interventions using withheld payments. In either case, we assume the penalty successfully motivates pessimistic providers to conduct all interventions and thus never pay the penalty. In practice, the ACO could discuss how to reallocate any penalty funds if this is not the case.

3.3.3. Numerical Results

To illustrate these mechanisms, suppose there is a network of 100 providers, each with 10 indicated patient interventions. Let the benefits and costs of these interventions be $b_{ij} = 5$ and $c_{ij} = 1 \forall i, j$. Pessimistic providers estimate probabilities of no readmission following intervention or abstention of $\Theta_{ij}^{(1)} = 0.75$ and $\Theta_{ij}^{(0)} = 0.7 \forall i$, whereas optimistic providers estimate $\Theta_{ij}^{(1)} = 0.9$ and $\Theta_{ij}^{(0)} = 0.7 \forall i$. The calculated mechanism fees given these inputs are $f = 0.25$ and $g = 0.75$. Figure 3-4 compares the utility by provider type (pessimistic or optimistic) for four alternatives:

- a. *Reassign*: Interventions for patients of pessimistic providers are evenly redistributed among all optimistic providers for a fee of $f = 0.25$ per intervention.
- b. *Outsource*: Interventions are reassigned to an outside vendor for a fee of $f = 0.25$ per intervention.
- c. *Penalty*: Providers in the network are penalized $g = 0.75$ for each intervention that is not conducted. We assume this sufficiently motivates pessimistic providers to conduct indicated interventions.
- d. *Do Nothing*: The current state where pessimistic providers do not conduct indicated interventions.

The first three alternatives correspond to the mechanisms outlined in the previous section to ensure that all indicated interventions are conducted. The fourth alternative corresponds to the current state where pessimistic providers do not conduct indicated interventions. Three scenarios (Table 3-2) were evaluated for their effect of provider type composition on the group outcome (primarily optimistic providers, primarily pessimistic providers, evenly split).

Table 3-2. Scenario parameters for pessimistic providers, optimistic providers, and interventions conducted under *Do Nothing*

Scenario	Pessimistic Providers	Optimistic Providers	Interventions If <i>Do Nothing</i>
Scenario 1	20	80	80%
Scenario 2	50	50	50%
Scenario 3	80	20	20%

For each scenario, Figure 3-4 summarizes the utility to each provider type (left hand side) and the percent increase over the current state (right hand side), relative to what could have been achieved in the ideal scenario with patients receiving all indicated interventions (denoted by dashed lines). As shown, the results of the three mechanisms approach the ideal scenario utility values and each mechanism is Pareto efficient to the alternative *Do Nothing* for both optimistic and pessimistic providers. Optimistic providers naturally achieve greater expected utility when more interventions are performed. Pessimistic providers achieve greater expected utility when the benefit of interventions conducted by the rest of the group is greater than the individual cost to conduct intervention, as in this example. Note that all three mechanisms achieve similar results, so subsequent figures average the effect of the three mechanisms. The improvement over *Do Nothing* and any alternate solution, furthermore, becomes more significant in cases for which there are more pessimistic providers in the ACO.

Figure 3-5 illustrates how the average utility gains from each mechanism increase as a function of provider mix, assuming the above intervention effectiveness beliefs, with as much as a 30% improvement over *Do Nothing* when the majority of providers are pessimistic. The mathematical definitions of optimism and pessimism can be reformulated to find the belief threshold $\Theta_{ij}^{(0)}$ that distinguishes an optimistic provider from a pessimistic provider as a function of the benefit-cost ratio. Specifically, provider j is

$$\begin{cases} \text{Optimistic} & \text{if } \Theta_{ij}^{(1)} \geq \frac{c_{ij}}{b_{ij}} + \Theta_{ij}^{(0)} \\ \text{Pessimistic} & \text{if } \Theta_{ij}^{(1)} < \frac{c_{ij}}{b_{ij}} + \Theta_{ij}^{(0)} \end{cases}.$$

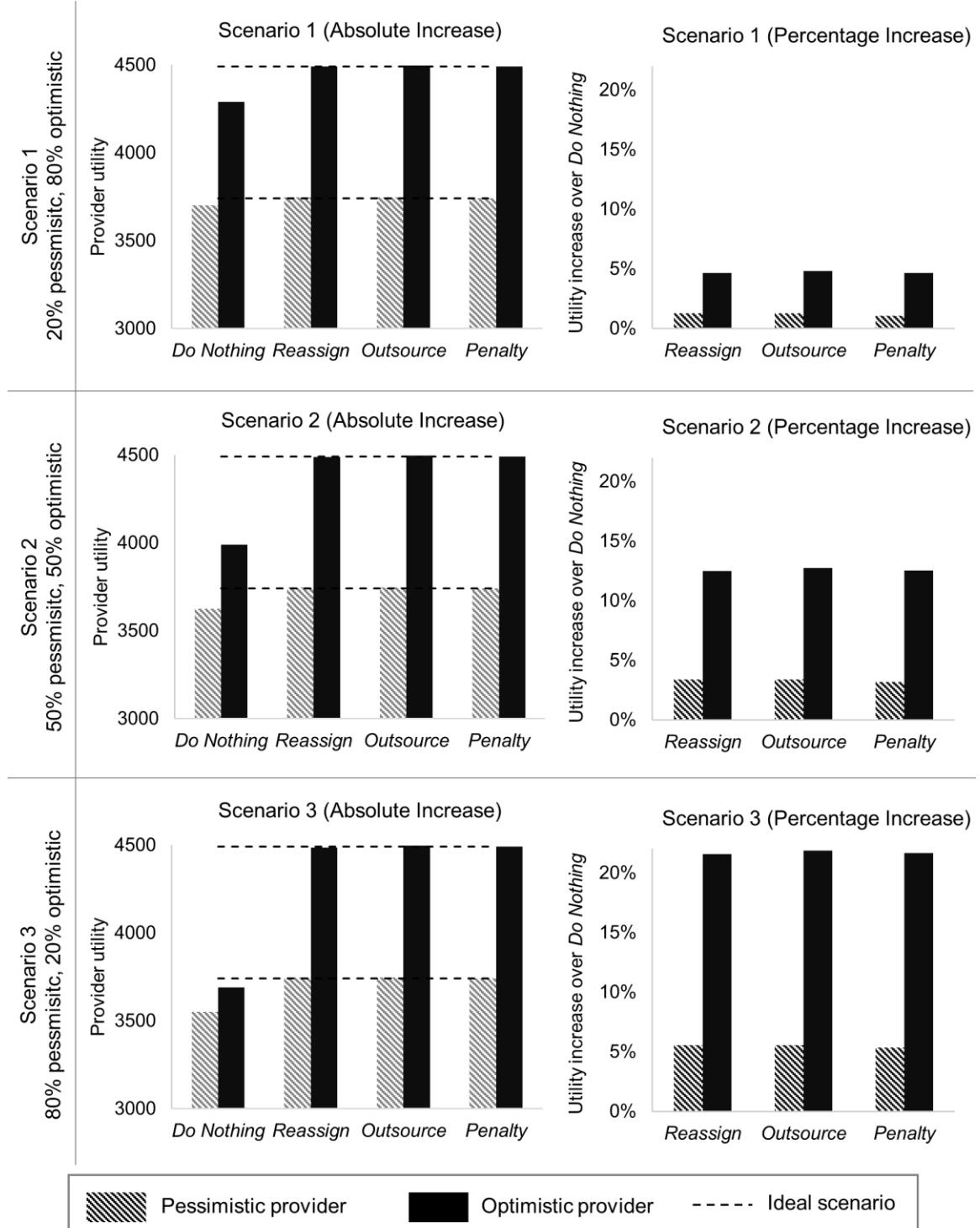


Figure 3-4. Effect of each mechanism on ensuring intervention and overall utility

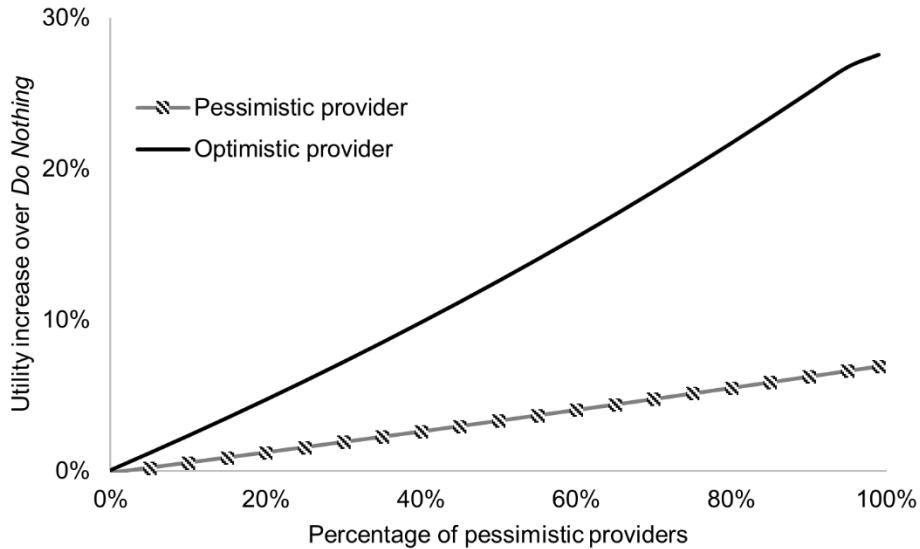


Figure 3-5. Average improvement in utility of the three mechanisms over *Do Nothing* as a function of the percentage of pessimistic providers

Figure 3-6 illustrates the nonlinear classification between optimistic and pessimistic providers over a range of benefit-cost ratios, assuming the estimated probability of no readmission without intervention is fixed at $\Theta_{ij}^{(0)} = 0.7 \forall i, j$. Figure 3-7 summarizes the average utility increase for the three provider type composition scenarios across a range of benefit-cost ratios (b/c) and provider belief in intervention effect ($\Theta^{(1)}$), where the gray shading indicates optimistic providers. Note that the calculation of f and g changes with the value of b/c . As shown, changes in provider belief have a large effect on the amount of utility improvement, whereas changes in benefit-cost ratios have little effect, presumably because the results are measured relative to *Do Nothing*. Finally, Figure 3-8 illustrates the effect of changes in provider belief on average utility improvement, assuming a benefit-cost ratio $b/c = 5$, which again can be significant as the percentage of pessimistic providers increases.

More broadly, all these results illustrate how ACO providers typically are better off in situations in which an incentive ensures all interventions are conducted. Results suggest an increase in utility relative to the current state for both optimistic and pessimistic providers under most conditions. The largest gains are realized by the most optimistic providers when the ACO as a whole is largely pessimistic.

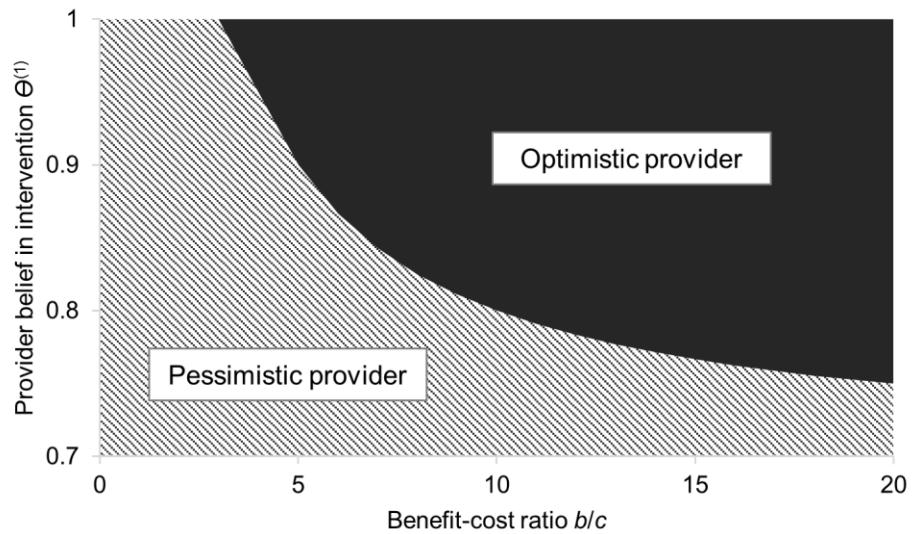


Figure 3-6. Impact of benefit-cost ratio and provider belief in intervention effect on classification of pessimistic and optimistic providers

		Benefit-cost ratio b/c									
		2	4	6	8	10	12	14	16	18	20
Provider belief $\Theta^{(1)}$	$\Theta^{(0)} = 0.7$	-0.2	-0.1	-0.1	-0.1	0.0	0.0	0.0	0.0	0.0	0.0
	0.75	1.1	1.2	1.2	1.3	1.3	1.3	1.3	1.3	1.3	1.4
	0.80	2.3	2.4	2.4	2.4	2.6	2.6	2.6	2.6	2.6	2.6
	0.85	3.3	3.4	3.5	3.7	3.7	3.7	3.7	3.7	3.7	3.7
	0.90	4.3	4.4	4.7	4.7	4.7	4.7	4.7	4.7	4.7	4.7
	0.95	5.2	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6	5.6
	1	6.0	6.5	6.4	6.4	6.4	6.4	6.4	6.4	6.4	6.4
		Benefit-cost ratio b/c									
		2	4	6	8	10	12	14	16	18	20
Provider belief $\Theta^{(1)}$	$\Theta^{(0)} = 0.7$	-0.2	-0.1	-0.1	-0.1	0.0	0.0	0.0	0.0	0.0	0.0
	0.75	3.2	3.3	3.3	3.3	3.4	3.4	3.4	3.4	3.4	3.5
	0.80	6.4	6.5	6.5	6.5	6.7	6.7	6.7	6.7	6.7	6.7
	0.85	9.3	9.4	9.5	9.7	9.7	9.7	9.7	9.7	9.7	9.7
	0.90	12.1	12.2	12.6	12.6	12.5	12.5	12.5	12.5	12.5	12.5
	0.95	14.7	15.3	15.2	15.2	15.2	15.2	15.2	15.2	15.2	15.2
	1	17.2	17.8	17.7	17.7	17.7	17.7	17.7	17.7	17.7	17.7
		Benefit-cost ratio b/c									
		2	4	6	8	10	12	14	16	18	20
Provider belief $\Theta^{(1)}$	$\Theta^{(0)} = 0.7$	-0.2	-0.1	-0.1	-0.1	0.0	0.0	0.0	0.0	0.0	0.0
	0.75	5.4	5.5	5.5	5.5	5.5	5.5	5.6	5.6	5.6	5.6
	0.80	10.8	10.9	10.9	11.0	11.1	11.1	11.1	11.1	11.1	11.1
	0.85	16.1	16.2	16.2	16.5	16.5	16.5	16.5	16.5	16.5	16.5
	0.90	21.2	21.3	21.7	21.7	21.7	21.7	21.7	21.7	21.6	21.6
	0.95	26.2	26.8	26.8	26.7	26.7	26.7	26.7	26.7	26.7	26.7
	1	31.1	31.7	31.7	31.7	31.6	31.6	31.6	31.6	31.6	31.6

Pessimistic provider
Optimistic provider

Figure 3-7. Average mechanism effect (percentage increase) across a spectrum of benefit-cost ratios (b/c) and provider belief in intervention effect ($\Theta^{(1)} \geq \Theta^{(0)} = 0.7$)

		Percentage of pessimistic providers									
		0	10	20	30	40	50	60	70	80	90
Provider belief $\theta^{(1)}$	$\theta^{(0)} = 0.7$	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1	-0.1
	0.75	-0.1	0.5	1.2	1.9	2.6	3.3	4.0	4.8	5.5	6.2
	0.80	-0.2	1.1	2.4	3.7	5.1	6.5	7.9	9.4	10.9	12.5
	0.85	-0.2	1.6	3.5	5.4	7.4	9.5	11.6	13.9	16.2	18.6
	0.90	0.1	2.3	4.7	7.2	9.8	12.6	15.5	18.5	21.7	25.1
	0.95	0.1	2.8	5.6	8.6	11.8	15.2	18.8	22.7	26.8	31.1
	1	0.0	3.1	6.4	10.0	13.7	17.7	22.1	26.7	31.7	37.1

Pessimistic provider
Optimistic provider

Figure 3-8. Average percentage change in utility as a function of provider belief in intervention effectiveness

3.4. Outcomes of the Mixed Strategy Equilibrium

3.4.1. Model Formulation

If an ACO does not assign primary responsibility and instead defaults to the mixed strategy equilibrium solution, the timing of an intervention may be relevant in preventing readmissions. Weesie [161] developed the volunteer's timing dilemma variation on the traditional volunteer's dilemma model, in which each player must decide when to volunteer if no other player has volunteered. In this sense, each provider has a continuum of waiting strategies from 0 to ∞ , implicitly committing to an action time when it will intervene if indicated care has not yet been provided. Assuming the patient is not readmitted first, the provider that commits to the soonest action time intervenes.

Weesie [161] suggests the probability of a favorable outcome is strictly decreasing over time. It is reasonable to suppose the patient's condition worsens over time, and so the probability of a favorable outcome worsens over time. We can alternatively imagine a concave function for the probability of a favorable outcome such that the intervention is most effective sometime after discharge but before the time of readmission. To simplify the preliminary analysis, we assume that when choosing an intervention time, the provider believes the intervention has a specified constant effect ϕ on the probability of a favorable outcome as long as the intervention precedes readmission. Note, however, that the probability of a favorable outcome is still nonincreasing over time as the population of intervention candidates (patients not yet readmitted) decreases over time.

Using the expanded notation in Table 3-3, suppose a_{ij} is the time t_i that maximizes the utility for provider j and let $a_i = \{a_{ij}\}_{j=1\dots N}$ be the set of all action times that each provider implicitly commits to. Then $a_i^* = \min\{a_i\}$ is the time at which the first provider will intervene. Likewise, let t_i^* denote the optimal time to intervene, when the probability of a favorable outcome is maximized. Figure 3-9 diagrams the basic decision process and probabilistic outcomes a provider must consider when choosing the action time for a given patient to prevent 30-day readmissions. Note each provider has incentive to delay a_{ij} to decrease $P_i(a_{ij})$, the probability of being the earliest provide.

Table 3-3. Notation for volunteer's timing dilemma model for ACO interventions to prevent readmission

Variable Definition

t_i	Time index for patient i ; $t_i \in [0, t_i^{\max}]$ where $t_i^{\max} \in [0, \infty)$
$R(t)$	Probability of readmission by time t without intervention
$\phi(t)$	Probability of favorable outcome at action time t
$P(t)$	Cumulative probability that time t will be the earliest action time
$p(t)$	Discrete probability that time t will be the earliest action time
$Q(t)$	Probability that time t precedes the time of readmission; $Q(t) = 1 - R(t)$
b_{ij}	Benefit to provider j with intervention at time t_i for patient i
c_{ij}	Cost to provider j to intervene at time t_i for patient i
a_{ij}	Action time at which provider j will intervene with patient i
s_{ij}	Binary variable that equals 1 if provider j intervenes for patient i

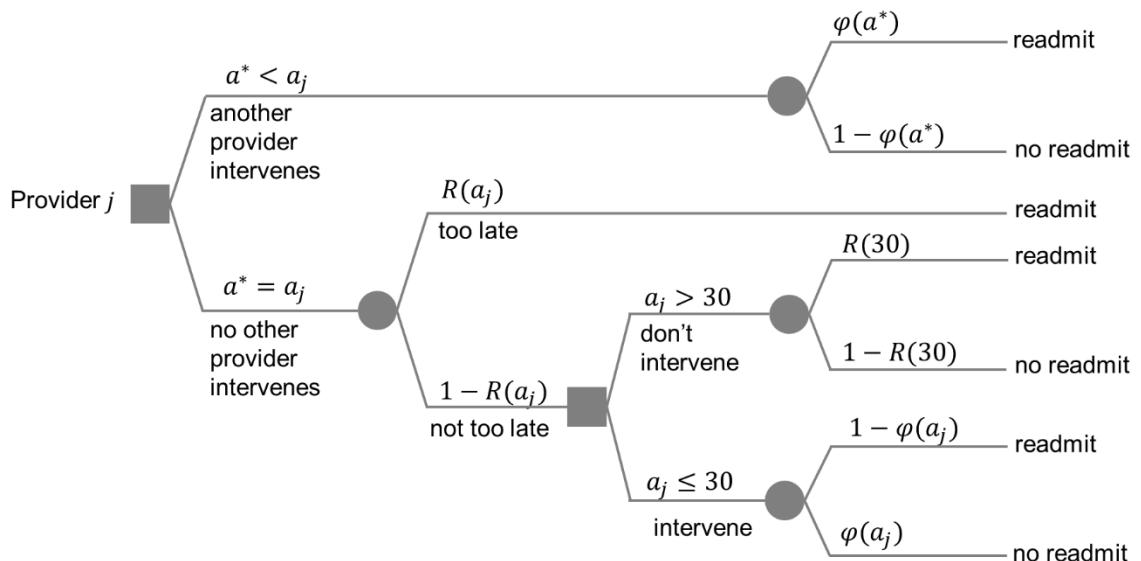


Figure 3-9. Decision tree and outcomes for provider j choosing intervention time a_j

Provider j chooses the action time a_{ij} that maximizes utility $U_{ij}(a_{ij})$ determined by the expected benefit of an intervention less the costs of intervening, or

$$\begin{aligned}
U_{ij} &= b_{ij}\phi(a_i^*) \sum_{k=1}^N s_{ik} - c_{ij}s_{ij} \\
&= b_{ij}\mathbb{E}\left[\phi(a_i^*) \sum_{k=1}^N s_{ik}\right] - c_{ij}\mathbb{E}[s_{ij}] \\
&= b_{ikj} \left[P(a_{ij})Q(a_{ij})\phi(a_{ij}) + (1 - P(a_{ij}))Q(a_i^*)\phi(a_i^*) \right] - c_{ij}P(a_{ij})Q(a_{ij}) \\
&= b_{ij} \left[P(a_{ij})Q(a_{ij})\phi(a_{ij}) + (1 - P(a_{ij})) \int_0^{a_{ij}} Q(t)\phi(t)dt \right] - c_{ij}P(a_{ij})Q(a_{ij}).
\end{aligned}$$

In general, we suppose that hospital decision makers act according to the day, and so prefer the discrete formulation for practical application

$$\begin{aligned}
U_{ij} &= b_{ij} \left[P(a_{ij})Q(a_{ij})\phi(a_{ij}) + (1 - P(a_{ij})) \sum_{t=0}^{a_{ij}} \frac{p(t)}{1 - P(a_{ij})} Q(t)\phi(t) \right] \\
&\quad - c_{ij}P(a_{ij})Q(a_{ij}) \\
&= b_{ij} \left[P(a_{ij})Q(a_{ij})\phi(a_{ij}) + \sum_{t=0}^{a_{ij}} p(t)Q(t)\phi(t) \right] - c_{ij}P(a_{ij})Q(a_{ij}).
\end{aligned}$$

Let $G(t)$ denote the expected probability of obtaining benefit b with action time t such that

$$G(a_{ij}) = P(a_{ij})Q(a_{ij})\phi(a_{ij}) + \left(1 - P(a_{ij})\right) \sum_{t=0}^{a_{ij}} \frac{p(t)}{1 - P(a_{ij})} Q(t)\phi(t)$$

and let $H(t)$ denote the expected probability of incurring cost c with action time t such that

$$H(a_{ij}) = P(a_{ij})Q(a_{ij}).$$

Similarly, let $v = b/c$ represent the benefit-cost ratio so that the utility formulation can be simplified to

$$U_{ij} = v_{ij}c_{ij}G(a_{ij}) - c_{ij}H(a_{ij}).$$

The utility maximization for provider j and patient i then can be formulated

$$\begin{aligned} & \max_{a_{ij}} \left(v_{ij}c_{ij}G(a_{ij}) - c_{ij}H(a_{ij}) \right) \\ & \Rightarrow c_{ij} \max_{a_{ij}} \left(v_{ij}G(a_{ij}) - H(a_{ij}) \right). \end{aligned}$$

Essentially, the maximum utility depends on the probability of earliest action time P , the readmission probability Q , the intervention effect belief ϕ , and the benefit-cost ratio v . In the context of this problem, we assume Q and ϕ are exogenous because the effort to affect the distribution of readmission times or intervention efficacy is distinct from the effort to control intervention timing. Although the effort to achieve optimal intervention timing will affect P , we also assume P is exogenous since this effect is indirect. The ACO controls the incentive structure, so we consider v endogenous such that the organization can realign incentives to achieve desired outcomes.

3.4.2. Numerical Results

Figure 3-10 summarizes the results of a scenario analysis that evaluates provider utility at different levels of ϕ , P , and v . The percentages under each line for $v \in \{2, 3, 4, 5, 6\}$ denote whether expected utility is maximized at $t = 1$ (left side) or $t = \infty$ (right side). The listed percentage indicates the percentage difference between choosing $a = 1$ and $a = \infty$. Based on empirical data, we defined a nonincreasing function for R such that 30% of the patient population is readmitted within 30 days of discharge. We fit P to an exponential distribution such that $100D\%$ of the patient population would receive an intervention within 30 days of discharge if the given provider chooses not to act, i.e. $(1 - P(30)) = D$. The expected utility of choosing an action time between day 1 and day 30 as well as choosing not to act were calculated for all configurations of $D \in \{0.1, 0.3, 0.5, 0.7\}$ and $\phi \in \{0.2, 0.4, 0.6, 0.8\}$. For the chosen parameters and distribution of P and R , the provider maximized expected utility at either $a = 1$ (intervening as soon as possible) or $a = \infty$ (never intervening). This corresponds with Weesie's finding that best response strategies concentrate probability mass in the earliest possible action time and ∞ [161], though we do not realistically expect providers to intervene only on day 1 if there are binding constraints on a high-resource intervention.

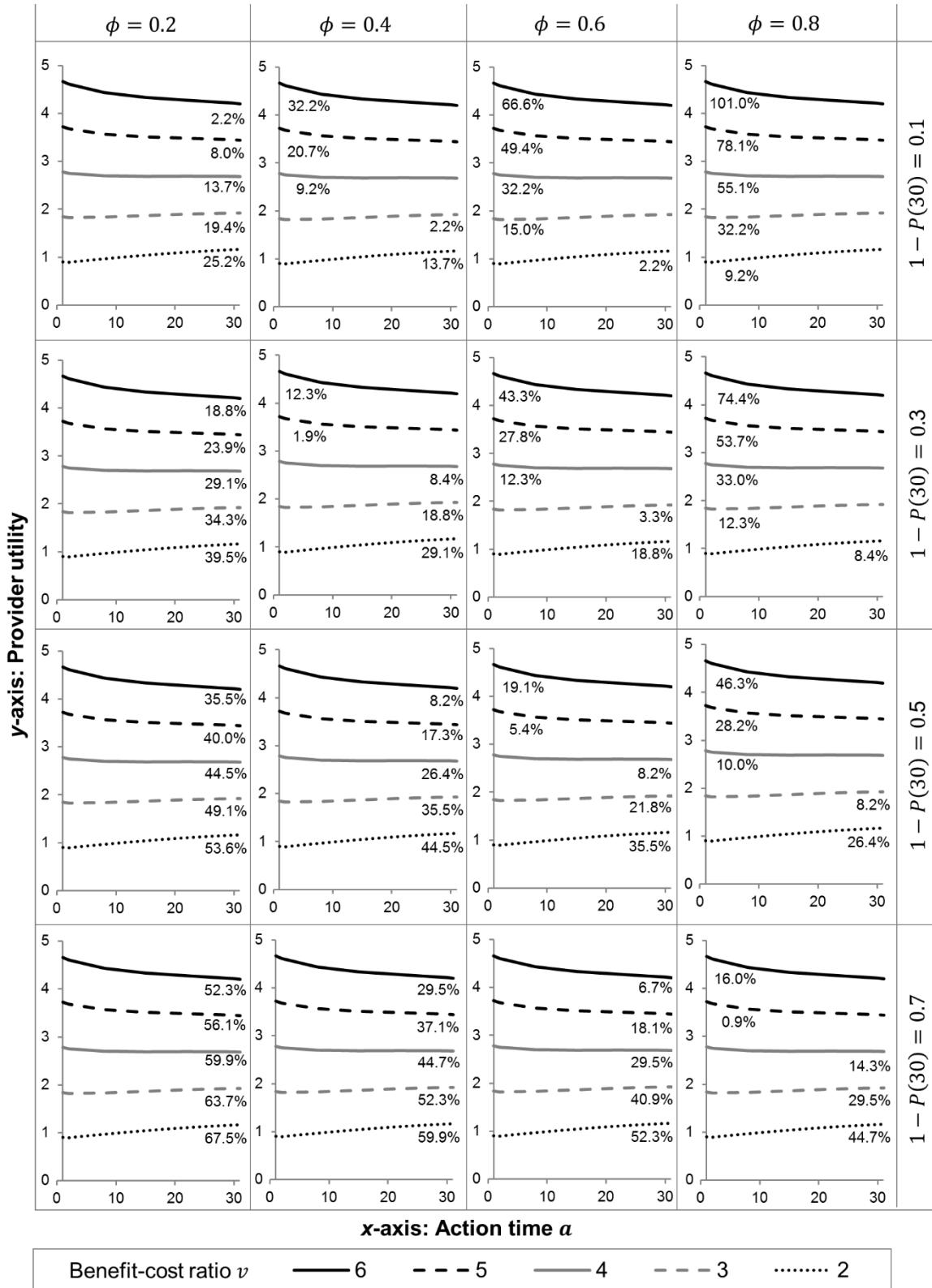


Figure 3-10. Expected provider utility as a function of action time a given intervention belief ϕ , likelihood another provider intervenes ($1 - P$), and benefit-cost ratio v

Observe that if belief in the effect of the intervention is low ($\phi = 0.2$), the benefit-cost ratio must be very high ($v > 6$) to entice the provider to intervene, especially if it is unlikely another provider will intervene. This is a concern for a coalition that expects providers to be accountable for patients discharged from the provider hospital. It may be cost-prohibitive to motivate the provider who believes readmissions are mostly inevitable for the provider's patient population to devote resources to interventions. Conversely, if the belief in the effect of the intervention is high ($\phi = 0.8$), the provider has sufficient incentive to intervene with a moderate benefit-cost ratio ($v \geq 3$) unless another provider is very likely to intervene.

Naturally, the ideal intervention is low-cost and highly effective. In the context of the volunteer's dilemma, the ACO must also consider the value system of the provider including the belief in the effect of the intervention and the estimation of how likely it is another provider will intervene. In designing the intervention program, the ACO then may achieve better outcomes by establishing clear guidelines under shared responsibility and seeking optimistic providers to conduct interventions. In this sense, the mixed strategy equilibrium may not be a practical solution for ACO operations whereas the asymmetric equilibrium solution concepts described in the previous section are more applicable in this context.

3.5. Discussion

Collaborative efforts in accountable care organizations and similar initiatives is a worthy concept with significant potential but also presents challenges to design systems that maximize this opportunity. As one example, this chapter explored how each provider's choice to conduct some readmission prevention intervention can be viewed as a volunteer's dilemma. Since payments to ACOs and other healthcare organizations are partially based on their performance to specified quality measures, the same general approach might be applied to evaluate other outcome measures as well, such as the other 32 quality measures in the CMS ACO model. Given variation in beliefs about each measure's effectiveness, it is helpful to consider how to ensure they are followed.

As shown, individual and ACO-wide utility can depend on each provider's belief in an intervention's effectiveness, with a sufficient percentage of pessimistic providers potentially leading to significant disutility. Individual accountability on these measures can be inconsistent since providers may disagree about how best to achieve the desired outcome. All three proposed mechanisms produce similar results, so choice in any given context can be somewhat based on which approach is more viable logically, culturally, or politically. While each mechanism may mitigate the volunteer's dilemma and increase utility for all providers across a network, each also has potential limitations. Reassigning interventions from pessimistic to optimistic providers may not be fully possible if the latter do not have extra capacity to conduct all additional interventions. Outsourcing interventions similarly may not be feasible if no external vendor can conduct

interventions at a sufficiently low cost, and penalizing providers that do not conduct indicated interventions also may be politically undesirable.

All three mechanisms also assume that the intervention actually does have value and that conducting all interventions is a worthy goal, whereas it is possible that pessimistic providers may have more accurately estimated the intervention's ineffectiveness. Finally, closely estimating the benefits and costs may be challenging. Nonetheless, understanding collaborative care from a volunteer's dilemma perspective can provide useful insight into incentives to intervene and ensure indicated care and prevention activities are provided.

Chapter 4. Fair Division in Incentive Design for Skilled Nursing Facility Care

4.1. Introduction

The fair division problem (also known as the "cake cutting problem") attempts to divide resources among participants with heterogeneous preferences so each recipient believes they have received a fair share. Fair division can counter the commons dilemma to ensure a cooperative solution that satisfies all partners and incorporates cooperation. The counterpart is chore division, where the objective is to divide responsibility for an undesirable resource to participants so that everyone believes they have not received an unfair share of the work. Chore division can be applied to minimize the effect of the volunteer's dilemma, assigning responsibility in such a way that every provider is able to treat patients in a timely manner. The focus on fairness and preferences differentiates the fair division framework from a typical optimization model.

We take a broad view of the fair division problem to account for payor and provider preferences in the design of value-based contracts. As an example, this approach can be used to incentivize skilled nursing facilities (SNFs) to provide quality care at a lower cost for patient populations with complex care needs. Although SNFs can provide less expensive care than costly inpatient care, payors must offer competitive reimbursement rates since SNFs can accept patients from multiple systems. Payors also should be willing

to pay higher rates to SNFs willing to enter into a risk-sharing agreement and meet certain value metrics, such as length of stay and subsequent hospitalizations, since these result in better outcomes at lower cost.

Typically a payor must negotiate fair terms of an incentive agreement with SNFs by either motivating them to improve performance in specific metrics or redirecting patient volume from low performing to higher performing SNFs. These options correspond to two incentive mechanisms that the payor controls:

- *Shared savings programs* to increase per diem rates for SNFs that improve performance in specified metrics, or
- *Preferred provider networks* to increase per diem rates for higher performing SNFs that are willing to accept a higher patient volume.

Since payment negotiations often can be confusing or arbitrary, this chapter develops two mathematical models to help identify mutually beneficial solutions that produce higher payments to the provider at lower cost to the payor. These include (1) a chance constrained optimization model that finds the optimal split for a shared savings program given a SNF's risk tolerance and variance in their value metrics and (2) an assignment algorithm that determines the maximum incentive for each potential preferred SNF willing to accept increased patient volumes. While described in the context of SNFs, the general approach and conclusions can be generalized to the design of value-based payments for a variety of other payors, provider types, and metrics.

4.2. Literature Review

4.2.1. Financial Incentives in Healthcare

The effect of financial incentives and how to best design them, while promising in certain cases, more broadly is somewhat inconclusive. A Cochrane review of 32 studies evaluating financial incentives found three types of methods generally effective for changing healthcare professional behaviors and patient outcomes [163]:

- Payment for each service, episode, or visit,
- Payment for providing care for a patient or specific population, and
- Payment for providing a pre-specified level of care or a change in activity care quality.

We focus on the third type of method, with 10 studies reporting improvement in 17 of 20 outcomes. Examples include incentives to improve immunization rates [164-166], increase cancer screening rates [167-169], improve diabetes care management [169, 170] improve smoking cessation clinical practices [171], and improve pediatric preventive care [172] along with a study that evaluated how financial incentives negatively affected patient selection [173].

Similarly, a review of 12 state-run pay-for-performance programs in the nursing home setting demonstrated little empirical evidence of improved quality or efficiency of care for nursing home residents [174]. Common observed problems in nursing home care include hospital readmissions [175] and potentially avoidable hospitalizations [176]; failure to meet care planning and discharge planning requirements [177]; inappropriate billing (estimated \$1.5 billion in inappropriate Medicare payments in 2009) [178]; and

depression and behavioral problems [179]. A randomized control trial with 32 San Diego nursing homes, however, found that financial incentives improved patient outcomes, reduced hospitalizations, and decreased average length of stay for people with severe disabilities [180, 181]. In 2009, the Centers for Medicare and Medicaid Services launched the Nursing Home Value-Based Purchasing Demonstration in three states that rewarded nursing homes with high performance or significant improvement, based on a composite score of staffing, appropriate hospitalizations, minimum data set outcomes, and survey deficiencies. While some cost savings were achieved, the study concluded that the demonstration project did not directly lower Medicare spending nor improve quality for nursing home residents [182]. We consider the application of fair division to design effective financial incentives.

4.2.2. Fair Division

Fair division theory was first developed by Steinhaus, Knaster, and Banach. Steinhaus [183] credits the "divide and choose" method to Banach and Knaster and helped contribute to the generalizations of the problem known as the "lone divider" method and "last diminisher" method. Gardner [184], Dubbins and Spanier [185], Stromquist [186], Austin [187], and Gale [188] contributed in defining the problem and how best to achieve an envy-free solution in which each participant prefers his allocation to all other allocations. The design of an algorithm that could successfully produce an envy-free solution for more than three players remained an open problem until Brams and Taylor [189] developed an envy-free protocol for four or more players and became the foremost experts in the field [190, 191].

There are several notable examples applying fair division techniques to real-world problems. Hill [192] and Beck [193] considered how to define border lines between neighboring countries. Su [194] outlined a procedure to partition rent among roommates. And of particular interest to our work, Varian [195] framed the fair division problem in terms of allocations in a coalition setting. We apply fair division techniques and the chance constrained programming method introduced by Charnes and Cooper [196] to design value-based contracts in the context of SNF care that account for heterogeneous provider preferences.

4.3. Chance Constrained Shared Savings Model

4.3.1. Model Formulation

The objective of the first model is to choose a shared savings split using that will appeal to both the payor and SNF by ensuring with high likelihood that

- The SNF receives a daily payment rate per patient greater than under their existing payment arrangement and
- The payor pays total costs per stay (including SNF stays and hospitalizations) less than under their existing payment arrangement.

Using the notation defined in Table 4-1, we develop a chance constrained optimization model that identifies the optimal division of shared savings with focus on reducing both lengths of stay at a SNF and hospitalizations after discharge from the SNF.

Table 4-1. Notation for SNF shared savings chance constrained programming model

Variable	Definition
D	Length of SNF stay in days (approximated as a normal random variable)
H	Hospitalization rate, i.e. the probability that a patient is hospitalized within 30 days after SNF discharge (different for each patient and approximated as a normal random variable)
f_D	Per diem rate for a SNF stay
f_H	Average fee for hospitalization of SNF patients
p_D	Proportion of savings paid to SNF for reducing length of stay
p_H	Proportion of savings paid to SNF for reducing hospitalizations

Letting D^0 and H^0 represent the average baseline levels of D and H from past performance, the daily payment per patient under the old payment system to a SNF is f_D . The new payment system adds all shared savings rewards to this base per diem rate to now have a daily payment per patient of

$$f_D + \frac{p_D f_D (D^0 - D)}{D} + \frac{p_H f_H (H^0 - H)}{D}.$$

To ensure this new rate is greater than under the old system, i.e.

$$f_D + \frac{p_D f_D (D^0 - D)}{D} + \frac{p_H f_H (H^0 - H)}{D} \geq f_D,$$

through simple algebra the following condition must be true

$$p_D f_D (D^0 - D) + p_H f_H (H^0 - H) \geq 0. \quad (4-1)$$

The expected total cost per stay for the payor under the old payment system is the sum of expected SNF stay costs and hospitalization costs, $f_D D^0 + f_H H^0$, whereas the new payment system includes any shared savings payouts,

$$f_D D + f_H H + p_D(D^0 - D) + p_H(H^0 - H).$$

To ensure the new total costs are less than under the old system, we set

$$f_D D + f_H H + p_D(D^0 - D) + p_H(H^0 - H) \leq f_D D^0 + f_H H^0.$$

The optimal values of p_D and p_H , the portion of shared savings paid to the SNF that minimizes total expected costs to the payor, then can be found such that a chance constraint satisfies Equation (4-1) with probability q as follows

$$\text{Minimize} \quad E(f_D D + f_H H + p_D(D^0 - D) + p_H(H^0 - H)),$$

$$\text{subject to} \quad P(p_D f_D(D^0 - D) + p_H f_H(H^0 - H) \geq 0) \geq q,$$

$$0 \leq p_D, p_H \leq 1.$$

Assuming D and H are normally distributed random variables, suppose Y represents shared savings payouts (also normally distributed) as a function of the proportions paid to the SNF p_D and p_H such that

$$Y(p_D, p_H) = p_D f_D(D^0 - D) + p_H f_H(H^0 - H).$$

The objective function of the optimization problem to find the shared savings split that minimizes total costs can be rewritten to isolate the random variables D and H ,

$$\begin{aligned} & E(f_D D + f_H H + p_D(D^0 - E(D)) + p_H(H^0 - E(H))) \\ &= f_D E(D) + f_H E(H) + p_D(D^0 - E(D)) + p_H(H^0 - E(H)). \end{aligned}$$

Given $Y(p_D, p_H)$, the expected value $E(Y)$ is

$$E(Y) = p_D f_D(D^0 - E(D)) + p_H f_H(H^0 - E(H)).$$

The variances of each term in the expected value formulation are

$$V(p_D f_D(D^0 - D)) = p_D^2 f_D^2 V(D)$$

and

$$V(p_H f_H(H^0 - H)) = p_H^2 f_H^2 V(H),$$

and their correlation is

$$\begin{aligned} & \text{Corr}(p_D f_D(D^0 - D), p_H f_H(H^0 - H)) \\ &= \text{Corr}(-p_D f_D D, -p_H f_H H) \\ &= \text{Corr}(D, H) = \rho_{D,H}. \end{aligned}$$

Since D and H may not be independent random variables, let Σ_Y represent the covariance matrix for Y such that

$$\Sigma_Y = \begin{bmatrix} p_D^2 f_D^2 V(D) & \rho_{D,H} p_D p_H f_D f_H \sqrt{V(D)V(H)} \\ \rho_{D,H} p_D p_H f_D f_H \sqrt{V(D)V(H)} & p_H^2 f_H^2 V(H) \end{bmatrix}.$$

The variance $V(Y)$ then becomes

$$\begin{aligned} V(Y) &= [p_D \quad p_H] \Sigma_Y \begin{bmatrix} p_D \\ p_H \end{bmatrix} \\ &= p_D^2 f_D^2 V(D) + p_H^2 f_H^2 V(H) + 2p_H p_D \rho_{D,H} f_D f_H \sqrt{V(D)V(H)}. \end{aligned}$$

The first constraint in the optimization model now can be rewritten as a chance constraint with $E(Y)$ and $V(Y)$ as the parameters of a standard normal distribution, where z_{1-q} is the standard normal score associated with tail probability q as follows:

$$P(p_D f_D(D^0 - D) + p_H f_H(H^0 - H) \geq 0) \geq q$$

$$P(Y \geq 0) \geq q$$

$$P\left(\frac{Y - E(Y)}{\sqrt{V(Y)}} \geq \frac{0 - E(Y)}{\sqrt{V(Y)}}\right) \geq q$$

$$z_{1-q} \geq -\frac{E(Y)}{\sqrt{V(Y)}}$$

$$z_{1-q}\sqrt{V(Y)} + E(Y) \geq 0.$$

A chance constrained programming model that finds the shared savings splits (p_D, p_H) that minimizes total costs to the payor then can be rewritten as

$$\text{Minimize} \quad f_D E(D) + f_H E(H) + p_D(D^0 - E(D)) + p_H(H^0 - E(H)),$$

$$\text{subject to} \quad z_{1-q}\sqrt{V(Y)} + E(Y) \geq 0,$$

$$0 \leq p_D, p_H \leq 1.$$

Using the above model, we can analyze a variety of scenarios to understand conditions that lead to successful shared savings programs attractive to both payors and SNFs.

4.3.2. Numerical Results

Consider an example in which the baseline average performance in length of stay and hospitalization rate are $D^0 = 20$ and $H^0 = 0.2$, respectively, the per diem rate is $f_D = \$350$, and the cost of a hospitalization is $f_H = \$12,000$. The baseline cost per subacute stay then is $f_D D^0 + f_H H^0 = \$9,400$. To comprehensively evaluate a number of scenarios, assume additionally that:

- Expected future performance is better than baseline performance, $E(D) \leq D^0$ and $E(H) \leq H^0$, such that expected results do not increase total costs,
- The payor sets a lower bound on expected performance at 75% of the baseline performance, $0.75D^0 \leq E(D) \leq D^0$ and $H^0 \geq E(H) \geq 0.75H^0$, to avoid incentivizing irresponsible reductions in lengths of stay and hospitalizations, and
- Improvements in SNF performance on both measures relative to increases in shared savings percentages are negative (i.e. $\frac{\partial D}{\partial p_D} < 0$ and $\frac{\partial H}{\partial p_H} < 0$) such that a SNF is assumed to achieve lower lengths of stay and hospitalization rates if given a larger portion of savings.

Let $r = (r_D, r_H)$ represent the target proportional reduction for D and H , respectively, such that $r = (0.1, 0.2)$ signifies a SNF wants to reduce their average length of stay by 10% and hospitalization rate by 20%. The below analysis examines combinations of $r_D \in \{0, 0.1, 0.2\}$ and $r_H \in \{0, 0.1, 0.2\}$ based on SNF preferences, resources, and an incentive function that links the magnitude of performance improvements to the size of the shared savings split.

The incentive function is assumed here to be linear in p_D and p_H such that

$$E(D) = D^0(1 - 2r_D p_D) \text{ and } E(H) = H^0(1 - 2r_H p_H),$$

where $p_D, p_H > 0$. Alternatively, if SNFs are indifferent to small incentives and mostly only respond to larger increases, this could be represented by a nonlinear response to p_D or p_H such that incentive functions are polynomial in p , for example

$$E(D) = D^0(1 - 2r_D p_D^2) \text{ and } E(H) = H^0(1 - 2r_H p_H^2),$$

assuming the polynomials are quadratic, or

$$E(D) = D^0(1 - 2r_D p_D^3) \text{ and } E(H) = H^0(1 - 2r_H p_H^3),$$

assuming the polynomials are cubic. If alternatively SNFs respond more to small increases, a nonlinear response to p_D or p_H could be represented with a square root function such that

$$E(D) = D^0(1 - 2r_D p_D^{0.5}) \text{ and } E(H) = H^0(1 - 2r_H p_H^{0.5}).$$

While not explored here, stepwise and other types of incentive functions also might be plausible. Figure 4-1 illustrates how SNF performance would change as a function of shared savings splits p_D and p_H given linear, quadratic, cubic, and square root incentive functions for reduction goals $r_D = r_H = 0.1$ and $r_D = r_H = 0.2$. As illustrated, under both polynomial incentive functions a SNF is not much motivated to improve performance for a small split of shared savings (roughly $p < 0.3$), whereas linear or decreasing incentive functions sufficiently motivate a SNF to improve performance even with a small percentage of shared savings.

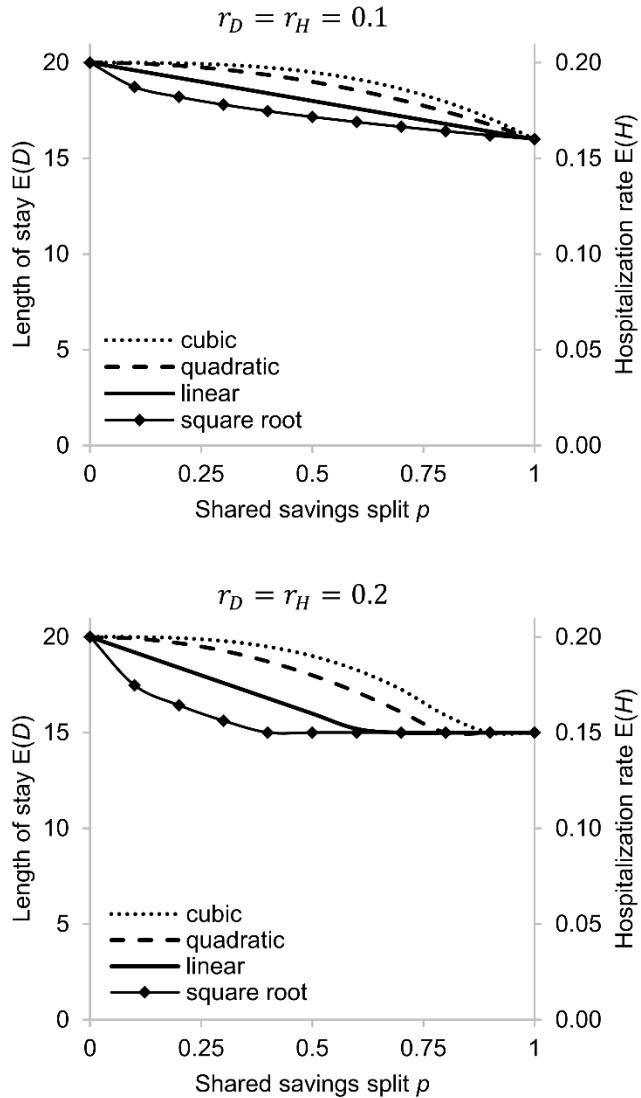


Figure 4-1. Impact of shared savings split p on length of stay and hospitalization rate performance for reduction goals $r_D = r_H = 0.1$ and $r_D = r_H = 0.2$ under linear, quadratic, cubic, and square root incentive functions given improvement is bounded $E(D) \leq D^0$ and $E(H) \leq H^0$

As further sensitivity analysis, two relationships for the variance of D and H were considered as functions of baseline performance and goal reduction targets

$$V(D) = (r_D D^0)^2 \text{ and } V(H) = (r_H H^0)^2$$

and

$$V(D) = (2r_D D^0)^2 \text{ and } V(H) = (2r_H H^0)^2.$$

Excel's optimization solver function was used to find optimal solutions for 1,920 variations of the chance constrained programming model for different incentive function shapes, variances, improvement goals, and probabilities that the new payment model will meet requirement. To do this, we first found the minimum cost solution for (p_D, p_H) when the chance constraint probability is removed ($q = 0$), implying the SNF has no risk aversion. The resulting minimum cost solution is $(p_D, p_H) = (0.5, 0.5)$ for configurations with a linear incentive function, $(p_D, p_H) = (0.67, 0.67)$ with a quadratic incentive function, $(p_D, p_H) = (0.75, 0.75)$ with a cubic incentive function, and $(p_D, p_H) = (0.33, 0.33)$ with a square root incentive function.

We found that these minimum cost solutions were feasible for all configurations where $q \leq 0.7$, so subsequent results focus on the feasible cost savings for scenarios with $q \geq 0.7$. As q increases, a SNF requires an increase in the shared savings split (p_D, p_H) , which is somewhat counterintuitive given the $(1 - q)$ probability that SNF performance worsens ($D > D^0$ or $H > H^0$), such that the SNF will receive a payment decrease proportional to shared savings splits (p_D, p_H) . However, this occurs because the expected increase in total shared savings in $100q\%$ of scenarios typically is large enough to offset this risk of a lower payment rate in the other $100(1 - q)\%$ of scenarios.

Figure 4-2 and Figure 4-3 illustrate the expected cost savings of a shared savings program (relative to the cost per subacute stay with no shared savings program) over $0.7 \leq q \leq 1$ for various combinations of improvement goals (r_D, r_H) . The best-case scenario is a low-variance SNF that assumes a square root incentive function and targets large reductions in hospitalizations ($r_D = 0.2$) and length of stay ($r_H = 0.2$). The payor could guarantee this SNF a per diem rate increase with probability $q > 0.95$ and achieve a 15% cost savings relative to the baseline cost per stay. The same 15% cost savings still could be achieved for a high-variance SNF but with less certainty on the guarantee ($q < 0.8$). With a strong guarantee ($q > 0.95$) to a low-variance SNF, the payor could achieve 10%, 6%, and 4% cost savings under a linear, quadratic, and cubic incentive functions. Note that in all scenarios, cost savings are mostly flat across a range of q and quickly decline to 0 after some threshold which can inform the discussion of risk tolerance.

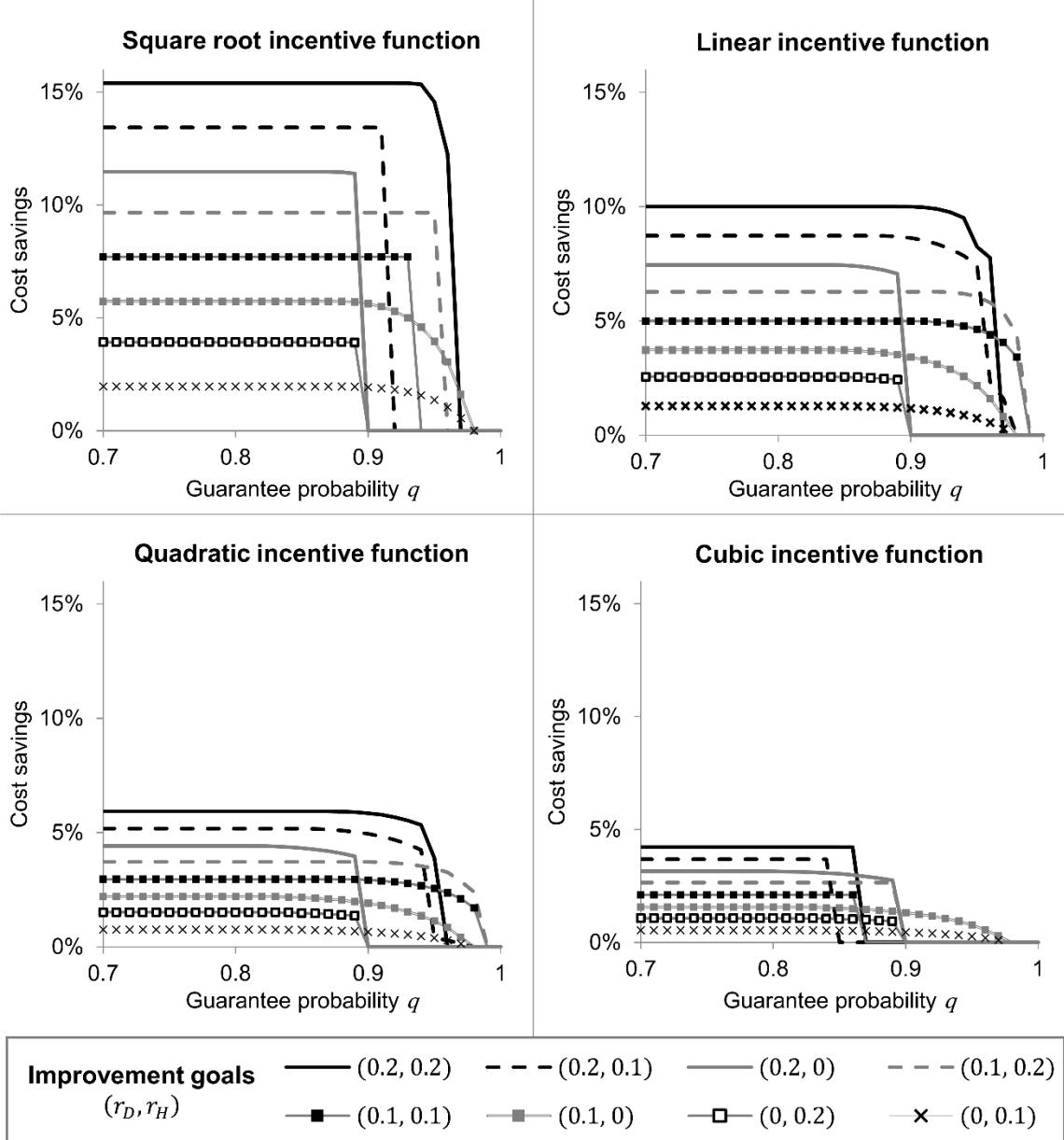


Figure 4-2. Expected cost savings as a function of chance constraint guarantee probability q given low SNF performance variance, incentive function shape (linear, quadratic, cubic, or square root), and improvement goals (r_D, r_H)

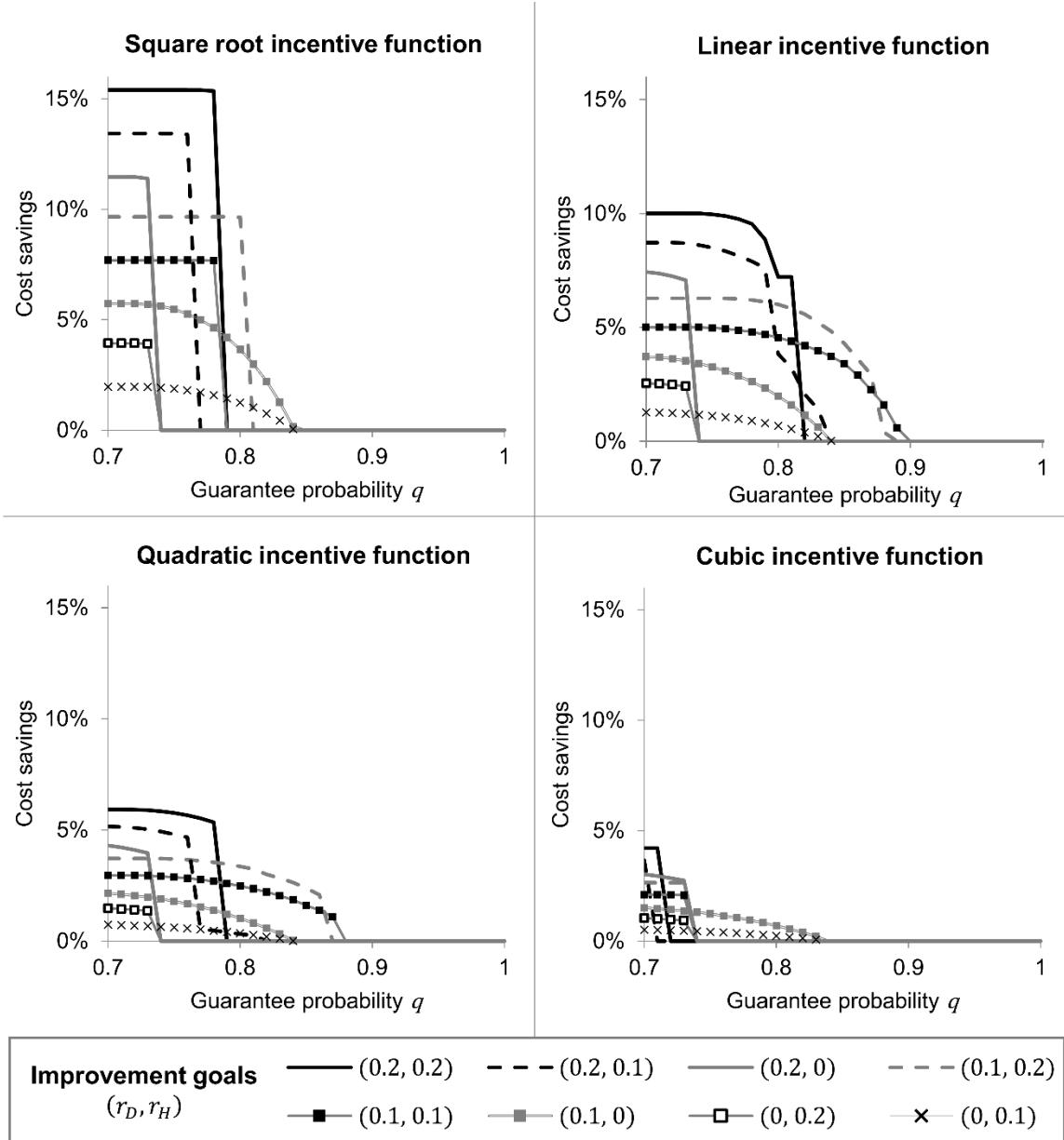


Figure 4-3. Expected cost savings as a function of chance constraint guarantee probability q given high SNF performance variance, incentive function shape (linear, quadratic, cubic, or square root), and improvement goals (r_D, r_H)

Figure 4-4 illustrates the expected cost savings averaged over the eight improvement goal combinations over the range $0.7 \leq q \leq 1$. As shown and is intuitive, the ideal SNF is low-variance (perhaps implying a large patient volume) and responds to smaller incentives with a square root or linear incentive function. In contrast, it arguably is not worth implementing a shared savings program with a high-variance SNF that only responds to larger incentives, unless the SNF is targeting large enough improvements in length of stay and hospitalizations to create a sufficiently large pool of shared savings.

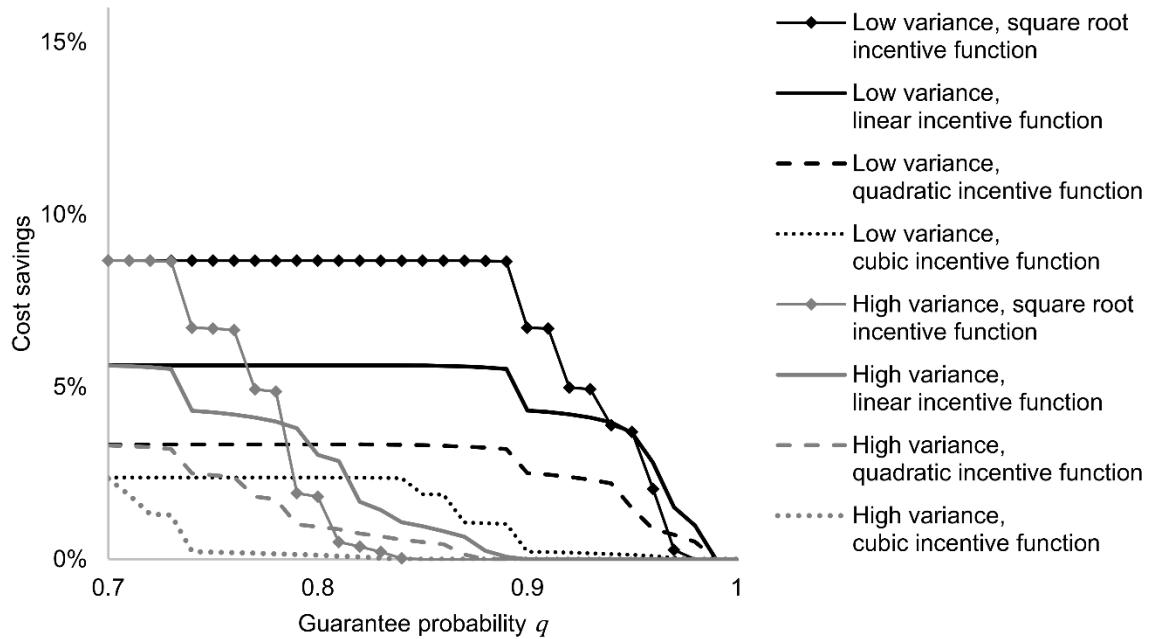


Figure 4-4. Average expected cost savings as a function of chance constraint probability q given SNF performance variance level (low or high) and incentive function shape (linear, quadratic, cubic, or square root)

4.4. Reallocation Assignment for Preferred Provider Network

4.4.1. Model Formulation

In parallel to the above, the focus of this second model is to redirect patients from “non-preferred” SNFs with high length of stay and hospitalizations rates (and thus higher costs) to “preferred” SNFs with lower rates and lower per stay costs, assuming that preferred SNFs will maintain quality performance under patient volume increases. Using the notation defined in Table 4-2, this can be formulated as an assignment problem.

Table 4-2. Notation for SNF preferred provider network reallocation assignment model

Variable	Definition
H_j	Hospitalization rate at SNF j
D_j	Average length of stay in days at SNF j
f_j	Per diem rate for SNF j
f_H	Average fee for hospitalization
n_j	Average number of patients placed in SNF j in a given year
x_{jk}	Binary variable that indicates whether SNF j and SNF k are close enough that a patient could feasibly be placed in either location
y_{jk}	Adjustment in average number of patients reassigned from SNF j to SNF k

Let n_j represent the average number of subacute stays at SNF j in the initial state and \hat{n}_j represent the average number of subacute stays at SNF j in the future state after reallocation. Likewise, let f_j represent the SNF j per diem rate in the initial state and \hat{f}_j represent the SNF j per diem rate in the future state. Since patient placement in SNFs is

constrained by geographical considerations, let \mathbf{X} represent an array that defines the allowable overlap between SNFs, such that element $x_{jk} = 1$ if a patient could be placed in either SNF j or SNF k and $x_{jk} = 0$ otherwise. The relative value of each SNF depends both on how that SNF compares to local alternatives and on its performance in the value metrics. SNF j may be a preferred provider if it accepts a preferred per diem rate \hat{f}_j that results in a per stay cost less than some local alternate SNF k , i.e. if

$$\hat{f}_j < x_{jk}(\hat{f}_k D_k + f_H H_k).$$

A SNF may achieve preferred provider status due to relative cost savings that can be attributed to low length of stay, low hospitalization rate, low baseline per diem rate, or some combination of these three factors. The decision variable y_{jk} indicates the change in the mean number of patients reassigned from SNF j to SNF k . The payor objective is to choose $y_{jk} \forall j, k$ to determine how to reallocate patient admitting volumes across the SNF network in order to decrease the total expected costs of all SNF stays, summed over all subacute stays

$$\sum_j \hat{n}_j (\hat{f}_j \hat{D}_j + f_H \hat{H}_j) = \sum_j \left(n_j + \sum_k y_{jk} - \sum_k y_{kj} \right) (\hat{f}_j \hat{D}_j + f_H \hat{H}_j).$$

Feasible reallocations are limited by several constraints:

- The number of patients assigned does not exceed a SNF's available capacity,
- The reassignment between SNF j and SNF k is geographically feasible given \mathbf{X} ,
- Reassignments will not result in a negative number of patients at any SNF, and
- Reassigned patient volumes between all pairs of SNFs are integers,

which can be written as

$$0 \leq n_j + \sum_k y_{jk} - \sum_k y_{kj} \leq C_j n_j \quad \forall j,$$

$$y_{jk} \leq M x_{jk} \quad \forall j, k,$$

and

$$y_{jk} \in \mathbb{Z},$$

where C_j represents a limit to the increase in patient volume that SNF j is willing to accommodate and M is a sufficiently large number. In practice, the payor must negotiate with each potential preferred SNF to find a per diem rate \hat{f}_j and feasible patient volume \hat{n}_j that is deemed fair by the SNF and that decreases total costs per subacute stay for the payor. To determine the limit of this negotiation, the above model calculates the maximum financial incentive level at which each potential preferred SNF maintains relative value compared to local alternatives.

The above assignment algorithm was implemented in Excel VBA to determine the maximum financial incentive level for each potential preferred SNF, incrementally increasing the per diem rate for each SNF as summarized by the pseudocode shown in Figure 4-5. If for a feasible reallocation of patient volume, SNF j receives $\hat{n}_j > n_j$ patients at per diem rate g then the maximum per diem rate for SNF j is at least $\hat{f}_j \geq g$. If instead $\hat{n}_j \leq n_j$ when SNF j is evaluated at per diem rate g , the maximum per diem rate is $\hat{f}_j < g$. Data inputs for each SNF include the mean number of patients in the initial state, per diem rate, average length of stay, and hospitalization rate (defined as the sum of qualifying hospitalizations divided by the number of subacute stays).

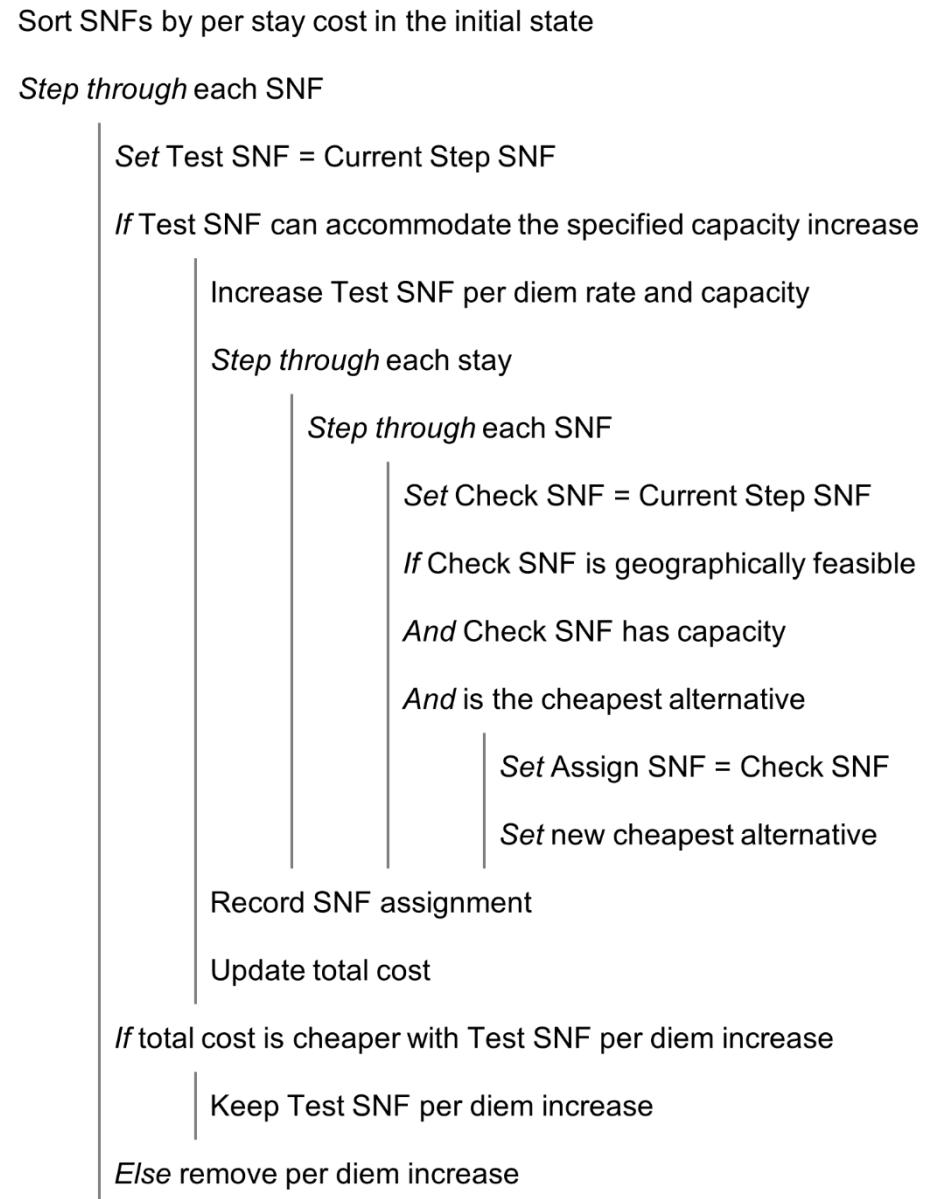


Figure 4-5. Logic of assignment algorithm to determine the maximum financial incentive level

4.4.2. Numerical Results

As an illustration, a representative payor provided 2013 data for 851 subacute stays at 92 SNFs in Massachusetts. The per diem rate for each SNF was estimated by dividing total subacute payments from 2013 claims data by the number of subacute stays. The distance between all 92 SNFs was calculated with Google Maps API to determine patient population overlap. To account for uncertainty in the mean lengths of stay and hospitalization rates given small sample sizes at certain SNFs, performance was classified into three tiers for average length of stay and hospitalization rate (low, moderate, and high). The data inputs for each tier classification are listed in Table 4-3. SNFs with fewer than 5 subacute stays in 2013 were assumed to belong to the moderate tier for both value metrics.

Table 4-3. Data inputs for each tier classification of average length of stay and hospitalization rate

Tier	Average length of stay (days)	Hospitalization rate
<i>Low</i>	16	10%
<i>Moderate</i>	20	20%
<i>High</i>	24	30%

Three factors were varied as part of a scenario analysis to determine patient placement and per diem rates in a preferred SNF network. The per diem rate was tested in increments of 3% such that SNFs received either a 0%, 3%, 6%, 9%, 12%, or 15% increase over the initial state per diem rate. Willingness to accommodate additional patient volume was tested with capacity increases of 10%, 20%, and 30% compared to the initial state. Finally, geographical feasibility with maximum acceptable distances for SNF volume reassignment was tested at 5 miles and 10 miles away from the initial state placement.

Figure 4-6 summarizes results for cost savings, length of stay decreases, and hospitalization decreases as a function of per diem increase and given acceptable distances of 5 miles (lefthand) or 10 miles (righthand). Note that as per diem rates increase, cost savings and hospitalizations are strictly decreasing but length of stay is non-monotonic. As shown, there is little apparent benefit in doubling the acceptable distance from 5 to 10 miles, implying that the marginal savings of expanding the set of alternative providers likely is not worth the travel inconvenience to patients. The solid lines represent a 30%, 20%, and 10% capacity increase, respectively. The dashed lines represent the negotiation scenario for which all providers accept their maximum financial incentive level in exchange for a 30% capacity increase. Since the 10% capacity increase provides minimal improvement, most SNFs that are not willing to increase capacity beyond that level have little leverage in negotiation.

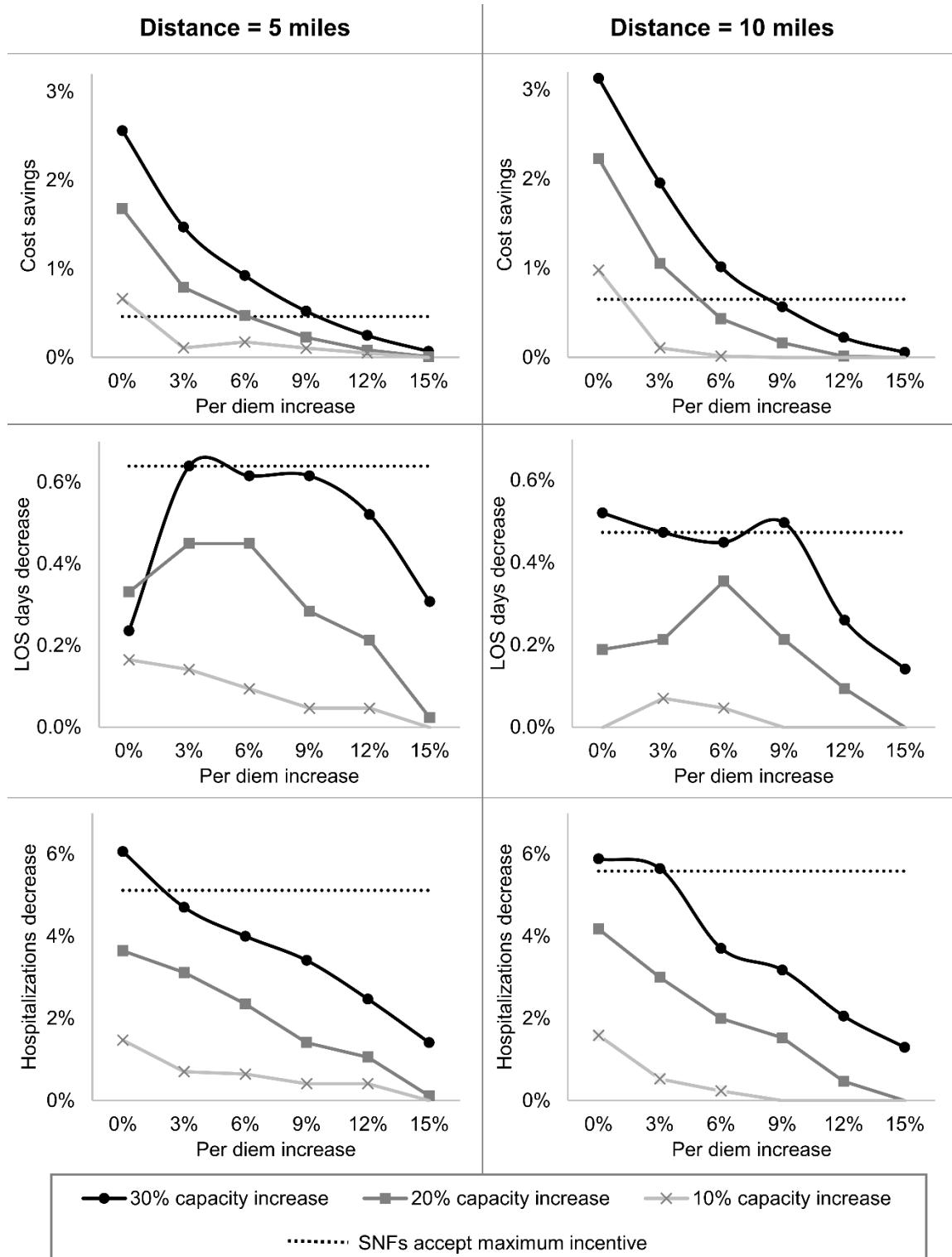


Figure 4-6. Cost savings, length of stay decreases, and hospitalization decreases as a function of per diem increase

While most scenarios generate cost savings less than 1%, notable decreases in length of stay and especially hospitalizations are apparent, and annual cost savings of 2-3% still are realistically feasible. As a thought experiment, suppose the shared savings program described in the previous section is effective in motivating length of stay and hospitalization rate decreases by 2% across all patients with a 50% shared savings split. We then conservatively estimate the joint implementation of a shared savings program (1% cost savings) and preferred provider network (0.2-1% cost savings) together could reduce annual costs to the payor by 1-2%. Greater cost savings are possible if the shared savings program produces greater quality improvements or the payor can establish a more favorable preferred provider network.

4.5. Discussion

While the design of value-based contracts can be challenging, payors and providers increasingly are adopting such plans in search of mutually beneficial solutions that decrease costs to the payor, increase payments to the provider, and improve outcomes for the patient. This chapter presented mathematical approaches to help identify the optimal splits for a shared savings program and financial incentive increases for preferred providers. Results also could be used as input to payor-SNF negotiations, complementing other quantitative and qualitative analyses.

While our analysis was informed by characteristics specific to skilled nursing facilities, this general approach also can be adapted to design shared savings programs and preferred provider networks for other care types. All value-based payment plans first

should ensure that a rational provider is better off providing quality care than alternatives associated with lower quality. Ideally, the payor can identify value metrics, such as length of stay and hospitalizations, in which quality improvements lead to lower costs. In such cases, the above mathematical models can help identify mutually beneficial results and help justify investments in quality improvement.

This approach has a few simplifications and limitations. For example, we viewed lower length of stay and fewer hospitalizations as a better outcome, but acknowledge certain patients require longer length of stay or hospitalizations to address poor health status. The described models also use quantitative inputs that may be difficult to estimate in practice, such as risk tolerance and incentive response functions. To account for this, we presented a range of quantitative inputs and suggested a qualitative classification that maps to quantitative inputs when possible.

While we decoupled the shared savings program and preferred provider network decisions, extension of this work could examine simultaneous optimization of these decisions. Future work also might consider how SNFs strategize patient mix when admitting patients from different payors. For example, SNFs may prefer Medicare fee-for-service patients which generally offer a higher rate to the Medicare managed care payor referenced in this chapter. However, SNFs also admit patients from payors with lower rates to ensure steady patient volumes and mitigate the risk of lost revenue due to empty bed-days.

Chapter 5. Conclusion

This dissertation presents an economic framework that links three game theory models to characterize healthcare market failures that lead to overtreatment, care coordination failures, and pricing failures. Mechanism design solutions can realign incentives to motivate better care at a lower cost for improved population health. To ground the theoretical framework, each chapter presents a real-world healthcare application related to the game theory models. Chapter 2 outlines how stewardship programs can design sustainable cooperative institutions to prevent a tragedy of the commons with antibiotic use. We also propose a tax formulation as an effective way to reduce inappropriate use, along with mathematical guidance to its optimal design. Chapter 3 discusses the volunteer's dilemma that can arise in accountable care organizations with an example in interventions to prevent readmission. We examine the necessary conditions for the stability of both the asymmetric and mixed strategy equilibrium solutions to the volunteer's dilemma and propose three mechanisms to help prevent failures in care coordination and ensure that patients receive indicated interventions. Chapter 4 provides mathematical modelling tools to negotiate fair financial incentives for a value-based contracts. This includes a chance constrained programming model to find the optimal split in a shared savings program and an assignment algorithm to determine the maximum financial incentive level for each potential preferred provider.

Our conclusions rely on utility theory, assuming rational decision makers will choose the strategy that maximizes a specified value function that represents preferences given alternatives. Quantifying inputs for meaningful calculation is challenging in a real-world context, especially when accounting for non-monetary benefits and costs in our interpretation of provider utility. The numerical results are sensitive to this limitation, so future research should consider how best to measure true provider incentives. For instance, inverse optimization techniques may help solve for feasible benefit and cost functions given observed behavior, while prospect theory and other behavioral economics methods may better account for situations where the decision makers are not strictly rational.

We also generally assume perfect information, when in fact providers may have reason to hide their preferences and the complexities of health insurance reimbursements do not always allow for cost transparency. So while we focus on problems for which there is consensus on an ideal group outcome that conflicts with rational individual strategies, there are certainly scenarios for which individual providers disagree about which strategy is ideal which may be better represented by Bayesian games that classify providers into distinct behavioral types. Similarly, providers must adapt strategies for each individual patient populations given heterogeneous patient populations, so dynamic models that allow for greater case mix variation may better reflect provider strategy variation.

In addition to these theoretical limitations, practical implementation could be challenging. Realigning incentives requires either a collective agreement between providers or a

central authority that can impose policy changes. Even if this can be accomplished at the organizational level, it must then be assumed that each organization can sufficiently incentivize individuals at the operational level to enact the organizational strategy. As a result, an alternative incentive structure that suggests a Pareto efficient solution in theory may not produce expected results. However, this research addresses problems in which providers, payors, and policymakers have identified suboptimal outcomes but are limited in process improvement by competitive equilibria, so the merit of this framework then is enabling the design of mutually beneficial cooperative solutions that can reward all involved parties if they are committed to change from current practices, behaviors, and policies.

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