PATIENT-CENTRIC INNOVATION IN SERVICE MODALITIES FOR END-STAGE RENAL DISEASE

by

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THESIS ABSTRACT

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The purpose of this study is to examine the feasibility of introducing innovative dialysis delivery methods. In the first essay, advised by Prof. Nagesh Murthy and Dr. Eren Çil, we study a new and non-traditional dialysis service modality, called a mobile dialysis clinic, that can reduce the travel burden for ESRD patients, resulting in a reduction in hospitalization costs undertaken by Medicare. To this end, we develop a framework to consider the strategic interaction between Medicare and a dialysis service provider and examine the potential benefit to Medicare for considering a "shared-savings payment policy." Specifically, our proposed incentive payment structure features "reward rate" as the percentage of hospitalization cost savings that the provider receives as a bonus payment for offering coverage using a mobile dialysis clinic. We first establish that the provider undertakes the additional costs of a new modality only when the reward rate offered by Medicare exceeds a critical level. We, then, show that once offering the new modality becomes viable, the provider serves more patients with the new modality and consequently decreases the hospitalization costs for Medicare as the reward rate increases. Despite the favorable effects of the new modality on the total hospitalization costs, Medicare faces a trade-off between lowering the hospitalization cost and the sharing cost savings with the provider. Hence, we find that Medicare does not always optimally offer enough compensation to the provider to justify offering the new service modality. However, we also identify certain conditions under which Medicare, interestingly, finds it optimal to increase the reward rate to incentivize the provider to offer a mobile clinic even when this increased reward rate results in a drastic improvement in provider's profit with only a marginal reduction in Medicare's cost.

We discuss the prospect of offering assisted home dialysis in the second essay to overcome the barriers to home dialysis. The second essay is advised by Prof. Nagesh Murthy and Dr. Eren Çil. Assisted home dialysis can be provided in-home or via telemedicine by a nurse. We develop a mathematical model to examine the implications of an optimal integration of new modalities, i.e., satellite clinics and nurse assisted home-dialysis into the existing dialysis network on the provider's profit and Medicare's costs. We analyze these implications under a variety of scenarios that reflect geographic dispersion of patients from the existing main clinic, patient preferences, and hospitalization cost attributed to recurring distance traveled. Our findings can help policymakers for Medicare design new policies that motivate providers to introduce new and innovative ways of offering dialysis to patients.

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CHAPTER I

INTRODUCTION

Every 30 minutes, the kidneys filter all blood and eliminate chemicals, waste, and excess fluid. Kidneys help the body to maintain its good health by stimulating the production of red blood cells and regulating blood chemicals. Chronic kidney disease (CKD) is a gradual loss of kidney function. Based on the kidneys' damage and their capability in filtering blood, CKD has five different levels. More than 15% of adults are estimated to have CKD in the U.S. [1]. CKD has no symptoms at early stages and should be diagnosed by blood test. 90% of patients with CKD are not aware of their disease until it reaches a critical level. CKD usually worsens over time. However, treatment can delay its progression. The last stage of CKD is called End-stage renal disease (ESRD). In the last stage, kidneys lose their entire function of removing waste products from the blood. Every day, more than 340 patients begin treatment for kidney failure [2]. The world's population ageing, extended life expectancy and the global diabetes mellitus epidemic are causing a dramatic increase in the number of ESRD patients [3]. While no solid statistics exist, it is estimated that 5.3 million of the global population had kidney failure in 2017 [4].

If ESRD is not treated, patients can survive a few weeks. Dialysis and kidney transplant are the two treatment options for kidney failure. Since the organ donation is limited, most patients rely on dialysis as the main treatment for ESRD.

Two principal types of dialysis are peritoneal dialysis (PD) and hemodialysis (HD). In peritoneal dialysis, a cleaning fluid is injected into a part of the patients' abdomen through a tube (catheter). The peritoneum (abdominal lining) acts as a filter, eliminating waste materials from the blood. After a certain amount of time, the fluid flows from the belly and is discarded with the filtered waste materials. In 2018, about 7.5%of ESRD patients were on peritoneal dialysis [5].

In hemodialysis, the patient's blood is pumped through the dialysis machine and special filters clean it before being pumped back into the body. Hemodialysis can be performed at a clinic or home. Most patients receive dialysis treatment at clinics that are managed by dialysis service providers. A typical dialysis schedule for a patient is comprised of three sessions per week at a clinic, on alternative days, with each session lasting for 3-5 hours. In contrast, home hemodialysis (home HD) can offer ESRD patients the benefits of convenience, flexibility, and the associated improved quality of life. Despite these advantages, many systematic barriers exist that impede the successful and effective delivery of home HD in the U.S. [6]. In 2017, only 2% of hemodialysis patients in the U.S. were treated by home hemodialysis.

Despite the fact that dialysis avoids death from kidney failure, life expectancy is often short, hospitalizations are common, treatment burden is high, and health-related quality of life is poor [5]. Recently, there has been another surge in the number of patients who need dialysis due to COVID-19. Although the exact impact of COVID-19 on kidneys is not fully clear, five studies performed in the United States show 19%-43% of hospitalized COVID-19 patients developed Acute Kidney Injury (AKI). More than 50% of AKI patients required dialysis [7]. This growing number of patients would inevitably contribute to a rise in dialysis, which presents major economic problems for global healthcare systems. Statistics show that kidney disease is the ninth leading cause of death in the United States [2]. Furthermore, dialysis is an expensive treatment, with the cost of care rising rapidly. Each patient's hemodialysis treatment costs approximately $93,000 per year [8]. The Centers for Medicare & Medicaid Services (CMS) have suggested adjustments to the Medicare End-Stage Renal Disease Prospective Payment System in order to mitigate the cost increase [9].

The new framework would encourage nephrology teams to reduce costs and enhance dialysis results by providing new treatment options for patients with renal disease. The agenda of this new policy is currently being developed by federal government officials, with feedback from specialists, but this plan offers a platform and resources for breakthrough innovation in dialysis treatment. The ESRD Treatment Options (ETC) payment model is another recent dialysis payment reform introduced by Medicare. The ETC model, recognizing the underutilization of home dialysis in the U.S., adapts payments to stimulate home dialysis [10].

The fundamental objective of this dissertation is to evaluate how Medicare's incentive strategies might be used to improve the dialysis network design through the introduction of innovative modalities. To address this challenge, two models are developed and analyzed in order to make recommendations to Medicare regarding potential approaches for strategic incentive designs for dialysis providers. The dissertation is separated into two articles, each of which examines a variety of critical questions that, when considered collectively, contribute to addressing the dissertation's overall question.

In the first essay of this dissertation, we explore the possibility of introduction of a new and non-traditional service modality that can reduce or eliminate the travel burden for ESRD patients while resulting in a reduction in hospitalization costs that can more than offset the added burden of supporting the operation of the infrastructure for the new dialysis modality.

This essay examines the economics and viability of introducing mobile clinics as a new mode of dialysis service delivery. We explore specifically the effect of Medicare's payment policy on the provider's decision to introduce this new modality.

Our study demonstrates that there is a reimbursement system under which a provider delivers a new modality that results in a net savings in overall hospitalization costs for Medicare, even after the provider receives a portion of the savings. It is possible to use equilibrium analysis to not only identify conditions under which a new modality is introduced, but also to determine the range of distances from the main clinic over which the new modality is introduced.

We have concentrated on the potential barriers in US for home HD in the second article, and to eliminate them, we propose that a professional caregiver (nurse) be present during the home HD session to perform or assist patients with dialysis. The nurse's engagement and support during dialysis reduces dialysis problems and increases patients' confidence in performing HD at home, as medical assistance is accessible if necessary. The purpose of the second essay is to determine the cost-effectiveness and feasibility of giving home dialysis assistance to patients who are currently undergoing dialysis. Nurses can assist patients in person or via telemedicine. Along with the option of in-home treatment, we consider the availability of satellite clinics. To investigate the cost-effectiveness, we developed a mathematical model for this problem and compared and evaluated the effectiveness of Medicare's incentive policy under a variety of operating factors, using various criteria and performance metrics.

The remainder of this dissertation is organized as follows. In chapter two, we review the existing literature related to dialysis delivery network and payment policies in healthcare operations. In chapter three, we present the analytical model and results of essay one. In chapter four, we present the mathematical model of essay two that is used to analyze the impact of home assistance and satellite clinics on the dialysis delivery network. Finally, we provide the concluding remarks in chapter five.

CHAPTER II

LITERATURE REVIEW

In this section, we review research in four main streams of literature that are related to this study. These streams are comprised of (1) studies at the interface of operation management and health economics that focus on the design of Medicare's reimbursement policies to elicit effective and efficient performance outcomes from health services providers; (2) studies directly focused on improving healthcare outcomes for ESRD patients; (3) research in ESRD care literature that examines the adverse effects of patients' residences being distant from the health service facilities; (4) OR/MS studies that focus on home healthcare delivery to patients. We provide a brief review of these four categories and discuss the contribution of our research vis-a-vis the literature.

The first stream of research is focused on the development of Medicare's reimbursement policies to incentivize health care service providers. Fuloria and Zenios [11] is one of the early papers to study a reimbursement strategy in a healthcare delivery system termed as outcome-adjusted payment (OAP) system. The authors employ a dynamic principal-agent model to determine how the OAP system motivates treatment choices that maximize total social welfare. The outcome-adjusted payment for a health provider consists of two parts: (1) a prospective payment per patient at the beginning of each period; and (2) an adjustment to the payment at the end of each period, according to the number of adverse events (e.g., hospitalizations, and deaths) observed during that period. Patients' health status evolves dynamically over time and can be influenced but not entirely determined by the provider's costly intervention efforts. Fuloria and Zenios present a numerical application of their model using Medicare's end-stage renal disease (ESRD) program and show that their proposed scheme leads to significant improvement in patient life expectancy. However, the implementation of the OAP system needs accurate information about patient characteristics and treatment technology that may not be readily available. Thus, they conclude that the implementation of a capitation system is more advisable than the OAP system. Capitation is a robust solution that achieves the majority of the efficiency gains associated with OAP.

In recent years, several researchers have focused on issues related to incentives in healthcare operations. Adiada et al. [12] analyze two main Medicare reimbursement strategies, namely, bundle payment (BP) and fee for services (FFS). They examine various reimbursement models to determine whether providers have an incentive to reject patients based on the anticipated cost of complications. The authors show that bundle payment strategy leads to sub-optimal results with a high risk for the providers and suggest strategies to improve this reimbursement scheme.

Andritsos and Tang [13] examine the effect of three different reimbursement schemes on readmission-reduction. They evaluate and compare fee for services (FFS), pay for performance (P4P), and bundle payment (BP) schemes from the perspective of health funder to determine the dominant scheme that can transfer the financial risk associated with re-hospitalization to the healthcare provider, while explicitly accounting for the effect of patient behavior. They develop a novel model of patient readmission considering the fact that patient care is jointly produced by the hospital and the patient's efforts. Their analysis shows that transforming some of the financial risks of readmission to the provider is more effective in inducing readmission reduction efforts. Based on their analysis, the FFS model is not an appropriate reimbursement mechanism in readmission-reduction programs. However, BP and P4P induce readmission reduction efforts. They show that when co-productive relation between provider and patient is weak, P4P tends to induce considerably more effort for readmission reduction than BP. However, BP is more effective once the strength of co-productive relation is above a threshold.

Guo et al.[14] characterize the effect of bundle payment (BP) and fee for services (FFS) schemes on performance measures, including revisit rate and waiting time for elective care services in a public health system. They model the interaction of patients, a healthcare provider, and a single funder in a three-stage Stackelberg game framework. The funder cares about the welfare of patients as well as the burden on external systems caused by the overflow of patients. At the same time, the healthcare provider maximizes her profit by choosing the service rate. Patients' decision to join the elective care system is embedded in the game with a queuing model. They consider two scenarios wherein patients are partially covered or fully covered. Their analysis shows the condition under which BP scheme dominates FFS scheme in terms of social welfare and revisit rate. Their results indicate that when the patient pool size is large, the bundled payment scheme dominates the fee-for-service scheme in terms of higher social welfare and a lower revisit rate. In contrast, the fee-for-service scheme prevails in terms of shorter waiting times. When the patient pool is small, the bundle payment scheme dominates the fee-for-service scheme in all performance measures.

The second stream of related literature is directly focused on improving healthcare outcomes for ESRD patients. Lee and Zenios [15] study Medicare's Quality Incentive Program (QIP 2010) for dialysis patients. The proposed payment strategy adds intermediate outcomes measurements to payment systems. They develop an evidence-based principal-agent framework to model the interaction of Medicare and a single provider to compare the QIP payment strategy with a new proposed payment strategy. They notice that the intermediate measures (dialysis dosage adequacy and anemia control) identified by Medicare as the main criteria for QIP 2010 are not comprehensive enough. Their proposed payment strategy, which is based on risk-adjusted downstream outcomes, is more effective and can increase patients' life expectancy without increasing Medicare's expenditure.

Skandari et al. [16] develop a dynamic model to find the optimal type of vascular access for dialysis patients that maximizes patients' probability of survival and adjusted quality of life. They study two types of vascular access, i.e., arteriovenous fistula (AVF) and central venous catheter (CVC) and show that delaying AVF surgery decreases a patient's life expectancy and quality of life. However, there is a threshold depending on the number of past AVF failures after which central venous catheter (CVC) is optimal.

Klein et al. [17] develop a model for network design of dialysis facilities to minimize the travel distance for the patients in the presence of budget and capacity constraints. They administer a patient preference survey to understand whether patient's preference for dialysis service at main or satellite clinics vis-a-vis at home is based on travel times, or is regardless of travel times. They subsequently incorporate the results of the survey as parameters into their mathematical model and show that with a given budget, it is possible to reduce the maximum and mean of patients' travel times.

Research in the third stream of related literature examines the adverse effects of ESRD patients' residences being distant from the health service facilities. Studies in the United States and other countries have found that longer driving times to dialysis clinics are associated with decreased quality of life, lower treatment attendance, and higher mortality rate for patients. Tonelli et al. [18] study a sample of 18,722 patients and find that the mortality associated with infectious causes is higher for hemodialysis patients who live farther from their attending nephrologist, when compared with those who live closer.

Rocco et al. [19] study the reasons for patients' absences from hemodialysis sessions and find that transportation difficulties are one of the most important reasons for missed treatments. Missed dialysis treatments are associated with increased risk for hospitalization that eventually contributes to rising healthcare costs [20]. Maripuri et al. [21] examine the relationship between distance from the dialysis unit and long-term mortality risk and observe increasing mortality risk for patients that live farther from their dialysis unit. Thompson et al. [22] show that remote residence is associated with increased mortality among patients initiating chronic hemodialysis treatment in the United States. Chao et al. [23] focus their study on the impact of travel distances to dialysis clinic and the development of health complications. They find that the risk of anemia increases with every 1 km increase in travel distance. Moreover, some studies find that shorter travel times to dialysis clinics increase patient satisfaction and quality of life. As an example, Diamant et al. [24] study the association between travel time to dialysis clinic and health-related quality of life (HRQOL) and find that travel cost and time are important factors to HD patients. They notice that HQOL is significantly higher for patients with shorter travel time to their dialysis clinic.

The fourth stream examines the growth and demand for home healthcare (HHC). To begin, a brief overview of the nurse rostering research is conducted. Then, we will take a look at a few articles that focus exclusively on ESRD. According to reports published by the Organization for Economic Cooperation and Development, population aging will lead to considerable growth in demand for health services. The growth of the world's population is projected to accelerate the industry's growth and increase patient demand for value-based healthcare. The World Health Organization (WHO) estimates 703 million people worldwide aged 65 years or older in 2019. By 2050, the global population of older people is expected to double to 1.5 billion. The aging population places a greater emphasis on patient-centered healthcare, which increases demand for healthcare staff and agencies and is expected to fuel business growth. Medicare is the biggest payer of home healthcare facilities in the United States. About 40 percent of home health expenditure accounts for Medicare expenses. Payments for medical assistance are divided into three primary categories: the standard (mandatory), home and community-based waivers, and home health care benefits. The market for home healthcare was worth USD 281.8 billion in 2019 and is forecast to expand at a 7.9 percent compound annual growth rate (CAGR) between 2020 and 2027.

In the home healthcare domain, public health planners face complicated and daunting optimization challenges at multiple decision-making stages, such as staff assignment, staff routing decisions, and shift scheduling. In most cases, the assignment of nurses to patients is required. Different criteria have to be taken into consideration to solve these issues, such as balancing nurses' abilities, patients' requirements, taking patients' interests into account, and various rules must be followed, such as the necessity of addressing the continuity of care. Furthermore, HHC services are very responsive to time. For example, care needs to be taken within a specific timeframe, such as various types of dialysis that make operations more complicated. A nurse is usually allocated to some patients who request several services over a specific period. Decisions on how and when to visit customers are the main obstacles for the planners, directly affecting travel and working times. As discussed by Fikar and Hirsch [25], the majority of home healthcare routing and scheduling papers are single-period problems. More specifically, a single working day is presumed as the planning horizon. When comparing these research papers, we observed that some papers establish planning protocols for the routing and coordination of nurses attending sessions at different health care centers and patients' homes. Patient requests are characterized by weekly frequencies or patterns in Shao et al. [26] and Bard et al. [27]. As mentioned earlier, working time regulations is another part of HHC's challenges. Several articles, such as Trautsamwieser and Hirsch [28], have studied a wide variety of compulsory breaks and work rules, including lunch breaks and compulsory weekly rest periods. Some scholars have studied uncertain environments, where not all information is known in advance. For example, Bennett and Erera [29] have examined an environment in which requests are randomly sent from patients for a series of weeks, and those requests must be visited by a predefined pattern.

Other relevant factors in the HHC articles include but are not limited to travel time/cost/distance, overtime work, precedence, and synchronization, where several nurses are expected to provide a service at the same time. To have a better understanding of the constraints, objective functions, and solution methods employed in this discipline, we refer readers to studies by Paraskevopoulos et al. [30], Fikar and Hirsch [25], and Erhard et al. [31].

Now we will review the publications that most closely match our settings. Using a mixed-integer linear programming model, Kandakoglu et al. [32] created a decision support scheme to improve day-to-day care routes and reduce home dialysis costs in a pre-specified group of patients. They also took into account the balance of nurses' workload, need for overtime breaks (lunch or dinner depending on shift hours), constraints and preferences associated with visiting periods, and various kinds of services available to patients. Data from the nephrological division at Ottawa Hospital were used to test the model. They show a noticeable improvement over the allocation of working load among nurses and a reduction in the overall distance traveled by nurses.

The problem of green delivery pick-up for Home Hemodialysis Machines (HHMs) as scarce commodities has been studied by Asghari, and Mirzapour Al-e-hashem [33]. The HHMs are supplied either from the company's central warehouse or from the actual shareholders. Based on the shared economy model, individuals who own HHM devices will participate in this home health care scheme and share the devices with others through the company's fleet to make money. After the portable HHM machines are delivered to the patients, they will be reused by a series of actions: a collection of machines, disinfection, and redistribution to the demand points. They use a bi-objective mixed-integer linear programming model to minimize total system cost and total carbon emissions. The model is named Torabi and Hassini's (TH) technique used to solve this problem, followed by development of multi-objective meta-heuristic algorithm, called self-learning non-dominated sorting genetic algorithm (SNSGA-II), for medium and large-sized problems.

Overall, our study contributes to the first research stream in the sense that we provide Medicare with a reimbursement policy to induce a healthcare provider to take actions that can reduce the total cost burden for Medicare. Additionally, our reimbursement structure is linked with patient welfare, which results in increased healthcare service quality for ESRD patients. The second stream has focused on the dialysis treatment level for enhancing the outcomes of dialysis care. At the same time, our research is also distinct from both the first and second streams of related literature since there is no previous research that has examined the role of reimbursement policy design for inducing a dialysis service provider to introduce new service modalities (e.g., mobile or satellite clinics), albeit costly, and yet aim to reduce the total cost for Medicare, while also improving health outcomes for ESRD patients. We incorporate key insights from the third stream of literature to design a reimbursement policy that focuses on mitigating a major driver of hospitalization cost for Medicare. The analytics in our strategic framework incorporates the adverse effects of patients' travel time on Medicare's cost in the dialysis service network. The majority of publications in the fourth stream offered a mathematical model without taking patient preferences into account. Additionally, most mathematical models do not examine the relationship between the provider, Medicare, and patients. Our suggested mathematical model is unique in that it incorporates both patient preference and the potential of offering home assisted dialysis in addition to other dialysis modalities. We discuss the details of the analytical framework in the following chapters.

CHAPTER III

ECONOMICS OF INTRODUCING A MOBILE CLINIC AS AN ADDED OR EXCLUSIVE MODALITY FOR DIALYSIS SERVICE

This work is coauthored with Prof. Nagesh Murthy and Dr. Eren Çil.

3.1 Introduction

In 2018, 3.6% of individuals with end-stage renal disease received a kidney transplant [34]. Due to the low rate of kidney transplantation, dialysis is currently the only viable option for the majority of patients. According to section 299I of Public Law 92-603, passed on Oct. 30th, 1972, Medicare covers dialysis treatment expenses, and any associated hospitalization cost for all ESRD patients [35]. Medicare takes overall coverage at the end of 30 months even for ESRD patients who have coverage from job-related insurance, retiree insurance, or COBRA. The scope and costs of the ESRD program have greatly exceeded the preliminary estimates envisioned in the early years of the program. This is largely due to the growth in ESRD patient population, and the cost of treatments [36]. According to the latest Annual Report of U.S. Renal Data, more than 750,000 Americans are being treated for ESRD [37]. The number of ESRD patients in the U.S. is growing at an annual rate of 4% [38]. This imposes a substantial cost burden on the government. Dialysis patients represent less than 1% of all patients served by the U.S. Centers for Medicare & Medicaid Services (CMS). However, their treatments account for 7% of all CMS expenditures [39]. In order to reign in the costs, Medicare has sought to revamp its payment systems to the dialysis service providers. Medicare implemented a bundled prospective system for dialysis patients in 2011 [40]. Despite such measures, ESRD spending per person per year (PPPY) has continued to increase annually at a high rate. In 2016, Medicare spending for patients with ESRD was nearly $35 billion [38].

While the total cost burden from recurring dialysis service accounts for the largest fraction of ESRD budget, the hospitalization costs incurred to cover ESRD patients in U.S. too is significant and accounts for about 33% of the ESRD expenditure [41]. Hence, in order to decrease hospitalization costs resulting from health complications for ESRD patients, it is critical to hone on factors that have adverse impact on their health outcomes.

Studies confirm that distance of patients' residence from health service facilities is inversely associated with clinical benefits to patients [42]. This adverse effect is specifically relevant and most likely exacerbated for ESRD patients as they have to travel to clinics for treatment between 140 and 160 times per year. An estimated 139 million one-way trips to dialysis clinics are needed annually to serve the population of ESRD patients in the U.S. Travel distance adversely affects access to care for ESRD patients more than most people, even when compared with other chronically ill patients with high health care utilization [43]. Studies show that patients who live far from dialysis facilities have worse outcomes [18]. Thus, recurring travel to dialysis clinics adversely affects patients' health, which in turn increases Medicare's costs due to the enhanced risk of health complications and ensuing hospitalization. Increased travel distance has serious clinical implications for ESRD patients and could have potentially adverse effects on patient mortality as well as their quality of life [44]. Thus, decreasing the travel distance for ESRD patients can significantly change their health outcomes and consequently decrease Medicare's cost.

In Oct. 2019, Medicare finalized some changes to ESRD reimbursements effective from Jan. 1st, 2020. The updated reimbursement scheme supports the development and use of innovative technologies: "CMS is establishing a transitional add-on payment adjustment to support the use of new and innovative renal dialysis equipment or supplies furnished by ESRD facilities" [1]. This essay is motivated by Medicare's renewed impetus to promote innovation in dialysis treatment and service delivery to reduce the overall cost burden for Medicare while improving treatment outcomes and quality of life for patients.

Our study examines the possibility of judicious introduction of a new and non-traditional service modality that can reduce or eliminate the travel burden for ESRD patients while also leading to a reduction in hospitalization costs that can reduce the additional burden associated with operating an infrastructure for the new modality for dialysis service.

The status quo service modality is comprised of a main clinic in a central location and operated by the service provider wherein all the ESRD patients assigned to the clinic travel to receive dialysis service at this clinic. We specifically examine whether, when, and how Medicare can benefit from incentivizing dialysis service providers to introduce state-of-the art mobile dialysis clinics as an additional service modality and stipulate the optimal coverage when introduced. The new dialysis service modality, called a mobile dialysis clinic, is a customized vehicle that is configured to house dialysis equipment identical to the ones used at the hemodialysis clinic and can move to a place near the patient's location. The quality of nursing care and other staff support for this new service modality is also considered to be comparable to that for the clinic. Thus, mobile dialysis clinic, as a new modality, can be configured to deliver high-quality treatment to ESRD patients.

Introduction of mobile dialysis clinic reduces the distance traveled by patients, which in turn reduces hospitalization costs incurred by Medicare. However, it is costly for the provider to introduce and operate the mobile dialysis clinic infrastructure. Hence, the provider needs an incentive payment to consider offering this new modality. It has been articulated in previous research that payment models can affect the type of service offered by the providers [45]. However, understanding the economics and viability of the introduction of mobile clinics as a new modality for dialysis service has hitherto not been considered in the academic literature or in practice. In this research, we develop a framework to consider the strategic interaction between Medicare and a dialysis service provider and examine the potential benefit to Medicare for considering a "shared-savings payment policy." In this policy, Medicare shares with the provider a fraction of savings realized due to reduced hospitalization cost on account of dialysis service coverage offered by the provider using mobile clinic service as a new modality. The specific range of distances from the main clinic over which the mobile clinic service is offered is used to determine the coverage for the ESRD patients as well as the added cost incurred by the provider to introduce and operate the new service modality. We allow for a special case of this new modality wherein no patients have zero travel, and it amounts to introduction of an additional clinic that is distant from the main clinic (i.e., a satellite clinic). The incentive payment structure in our new policy features "*reward rate*" as the percentage of Medicare's hospitalization cost savings that the provider receives as a bonus payment for offering coverage using a mobile dialysis clinic.

We specifically examine the role of Medicare's payment policy in influencing the provider's decision to introduce a new modality, which in turn affects patients' selection of service modality, and ensuing hospitalization costs. We model this strategic interaction in a game-theoretic framework that proceeds in three steps. First, Medicare selects the reimbursement contract that depends on modalities offered by the provider. Observing Medicare's contract and anticipating patients' decision, the provider offers the dialysis modalities and decides about the dialysis coverage. Finally, patients observe the available modalities and choose the one that decreases their travel distance. Therefore, patients' modality decision is endogenously determined.

Our analysis shows that there exists a reimbursement scheme (i.e., reward rate) for which the provider offers a new modality that results in net savings in total hospitalization cost for Medicare even after sharing some of the savings with the provider. We show that as the reward rate increases beyond a threshold, the provider serves more patients (i.e., offers a greater coverage) with the new modality, which in turn decreases the hospitalization costs for Medicare on account of reduced overall travel in the ESRD patient population. However, when the hospitalization cost is relatively low, Medicare does not offer enough compensation to the provider to justify offering coverage with a mobile clinic. In this case, for a low reward rate, the provider either just offers a satellite dialysis clinic (i.e., an additional clinic at a new location) or does not offer any new modality (i.e., prefers the status quo). Thus, Medicare faces a trade-off between hospitalization cost and sharing cost-savings with the provider. Interestingly, under certain conditions, we observe that Medicare finds it optimal to increase the reward rate to incentivize the provider to offer a mobile clinic even when this increased reward rate results in a drastic improvement in provider's profit with only a marginal reduction in Medicare's cost. Overall, our equilibrium analysis not only identifies conditions when new modality is introduced but also provides the specific range of distances from the main clinic over which the new modality is introduced. In our stylized modeling framework, this is akin to providing information on the location of a new facility (i.e., a satellite clinic) or route and coverage for mobile clinics in a dialysis service delivery network.

This paper makes the following contributions; first, we present a reimbursement scheme that centers on improving ESRD patients' health outcomes considering their travel distance to dialysis clinics. Second, we study the possibility of adding a new modality to the current dialysis network. Our analysis provides the condition under which introducing this innovative dialysis service is optimal. These findings can help CMS design new policies that motivate providers to introduce new and innovative ways of offering dialysis to patients. We review the relevant literature in Section 2. Section 3.2 provides our modeling framework and assumptions. Section 3.3 contains our key analytical results. A numerical analysis is provided for a robustness check in Section 3.4. Conclusions are provided in Section 3.5.

3.2 The Model Setup

In this essay, we study the strategic interaction between Medicare, a dialysis service provider, and ESRD patients. In the initial dialysis network, the dialysis provider operates a main clinic where it offers dialysis service to the patients who are heterogeneous in their location with respect to the main clinic. The status quo service modality is comprised of a main clinic in a central location and operated by the service provider wherein all the ESRD patients assigned to the clinic travel to receive dialysis service at this clinic. We specifically examine whether, when, and how Medicare can benefit from incentivizing dialysis service providers to introduce the mobile dialysis clinics as an additional service modality and stipulate the optimal coverage when introduced. In this research, we develop a framework to consider the strategic interaction between Medicare and a dialysis service provider and examine the potential benefit to Medicare for considering a "shared-savings payment policy." In this policy, Medicare shares with the provider a fraction of savings realized due to reduced hospitalization cost on account of dialysis service coverage offered by the provider using mobile clinic service as a new modality. The specific range of distances from the main clinic over which the mobile clinic service is offered is used to determine the coverage for the ESRD patients as well as the added cost incurred by the provider to introduce and operate the new service modality. We allow for a special case of this new modality wherein no patients have zero travel, and it amounts to introduction of an additional clinic that is distant from the main clinic (i.e., a satellite clinic).

The incentive payment structure in our new policy features "*reward rate*" as the percentage of hospitalization cost savings that the provider receives as a bonus payment for offering coverage using a mobile dialysis clinic. We specifically examine the role of Medicare's payment policy in influencing the provider's decision to introduce a new modality, which in turn affects patients' selection of service modality, and ensuing hospitalization costs. We model this strategic interaction in a game-theoretic framework that proceeds in three steps. First, Medicare selects the reimbursement contract that depends on modalities offered by the provider. Observing Medicare's contract and anticipating patients' decision, the provider offers the dialysis modalities and decides about the dialysis coverage. Finally, patients observe the available modalities and choose the one that decreases their travel distance. Therefore, patients' modality decision is

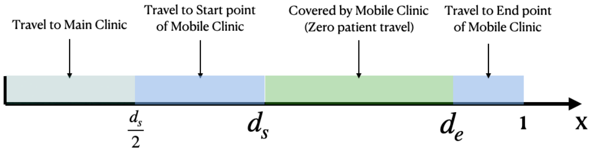


Figure 1. Patients' dialysis modality choice when mobile dialysis is offered from d_s to d_e

endogenously determined. We also assume that patients' locations with respect to the clinic are uniformly spread over the interval unit interval $[0, 1]$.

In this paper, we examine the viability of a new service modality for dialysis wherein the provider introduces a mobile dialysis service over the $[d_s, d_e]$ interval. We refer to this new modality as the "*mobile clinic*" and the $[d_s, d_e]$ interval as the "*mobile clinic range.*" We assume that the quality of dialysis care is identical in both the main and the mobile clinic.

Mobile dialysis service can be delivered practically at patients' locations via specialized vans, trucks, and busses. Therefore, we assume that the patients located inside the mobile clinic range do not incur any travel costs. As the patients value the main and the mobile clinic equally, patients inside the mobile clinic range always prefer to receive treatment at the mobile clinic. The remaining patients, on the other hand, are assumed to incur a positive cost proportional to the distance they travel to receive dialysis treatment. We do not restrict the service coverage of the mobile clinic to its range. Therefore, patients outside the mobile clinic range can choose between the main clinic and the end points of the mobile clinic range based on their distances to these three locations. In particular, each of these patients chooses to receive treatment at the closest of the three: the main clinic, d_s, and d_e. Note that it is sub-optimal for patients to request dialysis service from the mobile clinic at a location other than its end points. Figure 1 shows the changes in patients' coverage with a possible mobile dialysis service.

Medicare covers treatment costs for all ESRD patients [46]. We assume that the total regular payment made by Medicare to the provider for offering recurring dialysis treatment to the entire patient population is constant regardless of the service modalities. Another major component of Medicare's cost is driven by the hospitalization of the patients receiving dialysis. As mentioned before, patients' distance from dialysis facilities plays an important role in their overall health outcomes, including their likelihood of hospitalization. To capture the adverse effects of patients' travel on the hospitalization costs, we assume that Medicare incurs a cost of h_c per unit distance traveled by patients to receive dialysis treatment. Then, in the absence of a mobile clinic, we can write the Medicare's total hospitalization cost as:

$$H_o \equiv h_c \int_0^1 x dx = h_c/2.$$

On the other hand, when the provider offers a mobile dialysis clinic range of $[d_s, d_e]$, Medicare's total hospitalization cost becomes

$$\begin{aligned} H(d_s, d_e) &\equiv h_c \left(\int_0^{d_s/2} x dx + \int_{d_s/2}^{d_s} (d_s - x) dx + \int_{d_e}^{1} (x - d_e) dx \right) \\ &= h_c \frac{d_s^2 + 2(1 - d_e)^2}{4}. \end{aligned}$$

The above cost function is always lower than H_o as long as $d_e > 0$. Hence, mobile clinic decreases Medicare's hospitalization cost. However, the mobile clinic is a costly modality for the provider. In particular, we assume that the provider incurs

$$C(d_s, d_e) \equiv C_r(d_e - d_s) + C_d(1 - d_e + d_s/2),$$

Where the first term is the cost of serving the patients via the mobile clinic at their exact locations, and the second term is the cost of serving patients outside the mobile clinic range via the end points d_s and d_e. We refer to C_r as the "*range cost*" since it is the marginal cost of offering a mobile clinic range. Furthermore, C_d captures the incremental cost of serving patients at a distant facility rather than its main clinic, and thus, we refer to it as the "*distant-service cost.*"

Due to its range and the distant-service costs, for-profit providers will not find offering mobile dialysis profitable unless they are specifically motivated to do so. We assume that Medicare facilitates such motivation by committing to share α portion of its cost savings when a provider offers a mobile clinic. We refer to α as the "*reward rate.*" For any given reward rate α, a provider offering a mobile clinic range of $[d_s, d_e]$ receives a total reward of $\alpha[H_o - H(d_s, d_e)]$, and thus we can write the profit function of the provider as

$$\Pi_{Pro}(d_s, d_e; \alpha) \equiv \alpha[H_o - H(d_s, d_e)] - C(d_s, d_e). \tag{3.1}$$

3.3 Analysis

In this section, we study the optimal decisions of Medicare and the dialysis provider. We model the strategic interaction between Medicare and the provider as a sequential move game where Medicare first sets the reward rate α to minimize its total cost. Then, the provider chooses the mobile clinic range that maximizes its profits. We derive the outcome of the game between Medicare and the provider via backward induction. Thus, we first focus on the provider's problem.

3.3.1 The Optimal Mobile Clinic Range

As we mention above, we, first, characterize the provider's optimal mobile clinic range for any given reward rate α. To this end, we solve the following problem where the provider's objective is to maximize its profit, which is defined as $\Pi_{Pro}(d_s, d_e; \alpha)$:

$$\Pi^*_{Pro}(\alpha) \equiv \max_{0 \leq d_s \leq d_e \leq 1} \Pi_{Pro}(d_s, d_e; \alpha). \tag{3.2}$$

We denote the optimal decisions of the provider as $d_s^*(\alpha)$ and $d_e^*(\alpha)$ (d_s^* and d_e^* in short). As it can be seen in the above problem, the provider may find it optimal to set $d_s^* = d_e^*$. We refer to such special cases of mobile clinics as "*satellite clinic.*" A satellite clinic can be considered as a stationary, mobile clinic that does not serve any patients at their exact location. Note that a satellite clinic can still serve a significant portion of patients since it may be closer to these patients than the main clinic. Lemma 1 shows the minimum reward rate that incentives the provider to offer a new modality.

Lemma 1. *Considering costs of offering new modality, the provider makes decision with the goal of maximizing her own profit according to the reward rate (α):*

- *When $\alpha < \underline{\alpha}$, the provider does not offer new modality.*
- *When $\alpha \geq \underline{\alpha}(C_r)$, the provider has enough incentive to offer new modality, where*

$$\underline{\alpha}(C_r) = \begin{cases} 2C_r/h_c & \text{if } C_r < C_d/2 \\ \left(\sqrt{-\frac{C_d^2}{2} + 2C_dC_r - C_r^2} + C_r\right)/h_c & \text{if } C_d/2 \leq C_r < C_d \\ \left(\sqrt{-\frac{3C_d^2}{2} + 4C_dC_r - 2C_r^2} + C_r\right)/h_c & \text{if } C_d \leq C_r < (6C_d + \sqrt{3}C_d)/6 \\ (\sqrt{3}/2 + 1)C_d/h_c & \text{if } (6C_d + \sqrt{3}C_d)/6 \leq C_r \end{cases}$$

To guarantee the provider's participation, Medicare should offer a sufficient reward rate ($\underline{\alpha}$). $\underline{\alpha}$ is a non-decreasing function of range cost. This result is consistent with the intuition that provider needs higher motivation to offer new modality when the cost of offering new modality is higher. Using lemma 1, we can indicate the optimal decisions of the provider, presented in the following proposition.

Proposition 1. *For any $\alpha \geq \underline{\alpha}$, the provider optimally behaves in one of the following ways:*

- *The provider with* $0 \leq C_r < (6C_d + \sqrt{3}C_d)/6$ *offers new modality at* $d_s^* = \min\{0, \frac{2C_r - C_d}{h_c \alpha}\}, d_e^* = \max\{1 - \frac{C_r - C_d}{h_c \alpha}, 1\}$.
- *The provider with* $C_r \geq (6C_d + \sqrt{3}C_d)/6$ *optimally behaves in one of the following ways, depending on the reward rate* (α)*.*
  - *When* $(\sqrt{3}/2 + 1)C_d/h_c \leq \alpha < \frac{3C_r - 2C_d}{h_c}$ *the provider offers new modality at* $d_s^* = d_e^* = \frac{2h_c\alpha + C_d}{3h_c\alpha}$.
  - *When* $\alpha \geq \frac{3C_r - 2C_d}{h_c}$ *, the provider offers new modality at* $d_s^* = \frac{2C_r - C_d}{h_c\alpha}, d_e^* = 1 - \frac{C_r - C_d}{h_c\alpha}$.

Proposition 1 shows that for small values of the reward rate α, the provider would not have any incentive to incur the extra cost of new modality even if the mobile clinic range were chosen optimally. Therefore, the provider does not find offering a new modality profitable when α is small. When the reward rate increases enough to cover the new modality cost, offering a new modality becomes optimal. In particular, as α increases, the provider, first, chooses to offer a satellite clinic. Once the reward rate exceeds the critical level of $(3C_r - 2C_d)/h_c$, the provider optimally offers a mobile clinic range with $d_s^* < d_e^*$. We also show that as the reward rate increases, the provider serves more patients via its new modality. To achieve this, the provider moves either its satellite clinic or the starting point of its mobile clinic range closer to the main clinic. Figure 2 shows the location of the Satellite and a mobile clinic for a possible set of parameters.

As one expects, the cost parameters of the provider also play a significant role in the optimal decision of the provider. To be specific, the provider moves its satellite clinic farther from the main clinic as the distant-service cost C_d increases, and thus, it serves fewer patients via the new modality. The range cost also has a similar effect on the provider's optimal mobile clinic range: the optimal mobile clinic range shrinks as the range cost C_r increases, and the provider serves fewer patients with the new modality as it moves the starting point of the mobile clinic range farther from the main clinic. However, the distant-service cost C_d affects the provider's optimal mobile clinic range differently. We find that as C_d increases, the provider expands its optimal mobile clinic range and also serves more patients with the new modality by moving the starting point of the mobile clinic range closer to the main clinic. We also note that the hospitalization cost h_c, which is not a cost directly incurred by the provider, also affects the

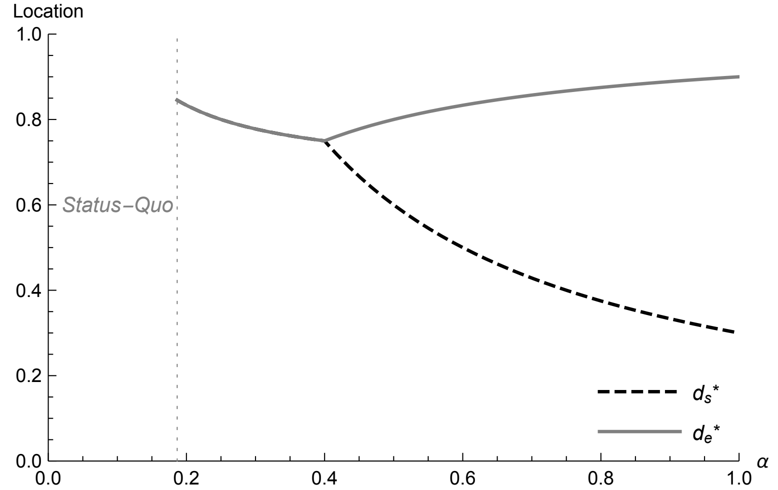


Figure 2. d_S^*, d_e^* as a function of the reward rate (α) when $C_r = 20, C_d = 10, h_c = 100$ and $d_S^* = d_e^*$ if provider offers satellite clinic.

provider's optimal decisions. Since Medicare shares its total cost savings with the provider, the provider responds in the same way to the changes in the hospitalization cost as it does when the reward rate α changes.

The above proposition presents the provider's optimal decision when the range cost C_r is above the critical level of $(6C_d + \sqrt{3}C_d)/6$. When C_r is lower than this critical level, the range of reward levels leading to a satellite clinic disappears, and thus we only observe the optimal decisions with $d_s^* < d_e^*$.

3.3.2 The Optimal Reward Rate

After studying the provider's problem, we now turn our attention to Medicare's decision. Anticipating the provider's optimal mobile clinic range, Medicare selects a reward rate α to minimize its total costs. As the total cost of Medicare includes the total hospitalization cost and the cost savings shared with the provider, we write Medicare's total cost as

$$\begin{aligned} \kappa_{Med}(\alpha) &\equiv H(d_s^*, d_e^*) + \alpha\big[H_o - H(d_s^*, d_e^*)\big] \\ &= \frac{h_c}{4}\Big[\big(2(d_e^* - 2)d_e^* + {d_s^*}^2\big)(1-\alpha) + 2\Big]. \end{aligned} \tag{3.3}$$

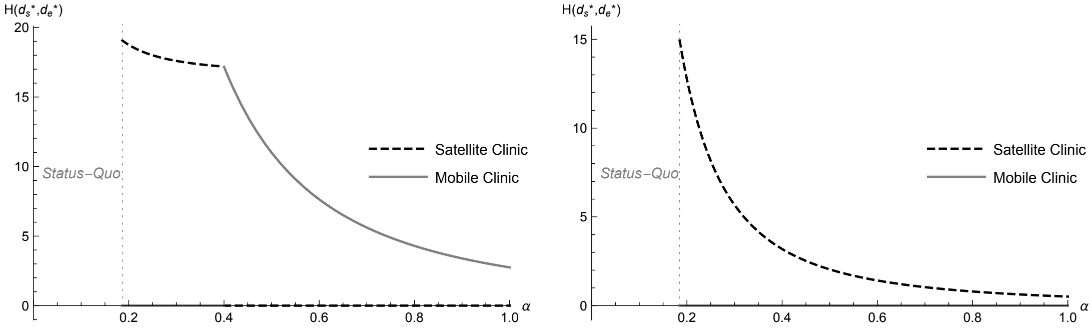
Then, we solve the following problem to find the optimal reward rate, which we denote as α^*:

$$\kappa_{Med}^* \equiv \min_{0 \leq \alpha \leq 1} \kappa_{Med}(\alpha). \tag{3.4}$$

As the hospitalization cost $H(d_s^*, d_e^*)$ is a crucial part of Medicare's total cost, we first focus on the effects of the reward rate α on the hospitalization cost before finding the optimal reward rate.

Proposition 2. *$H(d_s^*, d_e^*)$, Medicare's total hospitalization cost, is monotonically decreasing in α. Furthermore, $\alpha\big[H_o - H(d_s^*, d_e^*)\big]$, the cost savings shared with the provider, is monotonically increasing in α.*

In Proposition 2, we show that Medicare's total hospitalization cost decreases as Medicare offers a higher reward rate. The main driver of such a cost reduction is that the provider serves more patients via its new modality as the reward rate increases, as discussed after Proposition 1. As a direct implication of this cost reduction, the provider receives a larger total reward. Hence, while choosing its optimal reward rate, Medicare has to balance these two opposing effects of increasing the reward rate. Additionally, as Figure 3 illustrates, the hospitalization cost decreases at different rates depending on whether the provider offers a mobile clinic range or a satellite clinic, and thus has a piece-wise structure.



a) $C_r = 20, C_d = 10, h_c = 100$ **b)** $C_r = 12, C_d = 10, h_c = 100$

Figure 3. Medicare's hospitalization cost $H(d_S^*, d_e^*)$ as a function of the reward rate (α).

Due to the piece-wise nature of the hospitalization cost $H(d_s^*, d_e^*)$, Medicare's total cost $\kappa_{Med}(\alpha)$ also becomes a piece-wise function of the reward rate α. To be specific, as Figure 4 illustrates, $\kappa_{Med}(\alpha)$ is the combination of two convex functions where one convex function refers to a range of α leading to a satellite clinic and the other one is the range of α leading to a mobile clinic range.

As Medicare's total cost function may not always be quasi-convex, Medicare may need to find two locally optimal reward rates and compare these two in order to obtain the optimal

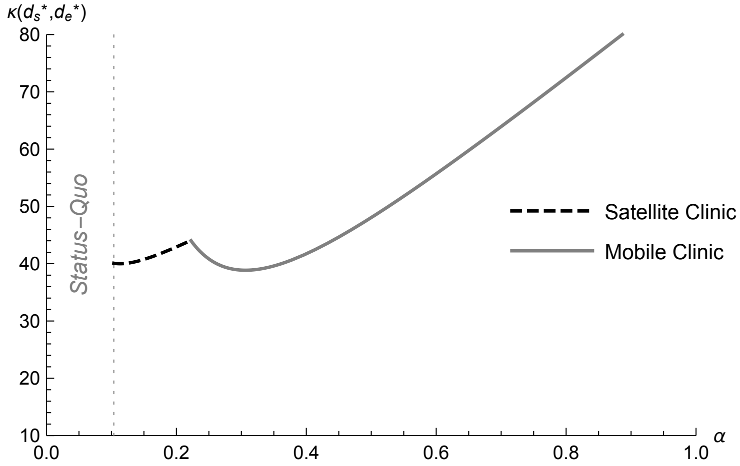


Figure 4. Medicare's total cost as a function of the reward rate (α) when $C_r = 20, C_d = 10, h_c = 180$

reward rate. In Proposition 3, we derive the conditions under which such a comparison is needed. We also derive the conditions under which motivating the provider to offer a satellite (a mobile) clinic is clearly dominated by motivating the provider to offer a mobile (a satellite) clinic.

Proposition 3. *For any combination of* C_r, C_d, h_c *we can characterize the Medicare and provider best responses as follows:*

– *if* $(C_r, h_c) \in \Omega_1$ *then* $d_s^*(\alpha^*) = d_e^*(\alpha^*)$ *and* $\Pi^*_{Pro}(\alpha^*) = 0$.

– *if* $(C_r, h_c) \in \Omega_2$ *then* $d_s^*(\alpha^*) = d_e^*(\alpha^*)$ *and* $\Pi^*_{Pro}(\alpha^*) > 0$.

– *if* $(C_r, h_c) \in \Omega_3$ *then* $\exists\ (\alpha_1^*, \alpha_2^*)$ *such that* $d_s^*(\alpha_1^*) = d_e^*(\alpha_1^*)$ *and* $d_s^*(\alpha_2^*) < d_e^*(\alpha_2^*)$

$$\textit{where } \alpha^* = \begin{cases} \alpha_1^* & \textit{if } \kappa_{Med}(\alpha_1^*) < \kappa_{Med}(\alpha_2^*) \\ \alpha_2^* & \textit{if } \kappa_{Med}(\alpha_2^*) < \kappa_{Med}(\alpha_1^*) \end{cases} \quad \textit{and} \quad \begin{cases} \Pi^*_{Pro}(\alpha^*) > 0 & \textit{if } \alpha^* = \alpha_2 \\ \Pi^*_{Pro}(\alpha^*) \geq 0 & \textit{if } \alpha^* = \alpha_1 \end{cases}$$

– *if* $(C_r, h_c) \in \Omega_4$ *then* $d_s^*(\alpha^*) < d_e^*(\alpha^*)$ *and* $\Pi^*_{Pro}(\alpha^*) > 0$.

where

- $\Omega_1 \equiv \{(C_r, h_c) : \frac{7\sqrt{3}C_d+12C_d}{4\sqrt{3}+6} < h_c < min\{4\sqrt{3}C_d + 7C_d, \frac{\sqrt{3}C_d+2C_d}{2h_c}\}, C_r > (6C_d + \sqrt{3}C_d)/6\}$.
- $\Omega_2 \equiv \{(C_r, h_c) : 4\sqrt{3}C_d + 7C_d < h_c < \frac{72C_r^3-144C_r^2C_d+97C_rC_d^2-22C_d^3}{12C_r^2-16C_rC_d+6C_d^2}, C_r > (6C_d + \sqrt{3}C_d)/6\}$
- $\Omega_3 \equiv \{(C_r, h_c) : \frac{72C_r^3-144C_r^2C_d+97C_rC_d^2-22C_d^3}{12C_r^2-16C_rC_d+6C_d^2} < h_c < \frac{108C_r^3-216C_r^2C_d+147C_rC_d^2-34C_d^3}{2C_d^2}, C_r > (6C_d + \sqrt{3}C_d)/6\}$.

- $\Omega_4 \equiv \{(C_r, h_c) : h_c > \frac{108C_r^3 - 216C_r^2 C_d + 147C_r C_d^2 - 34C_d^3}{2C_d^2}, C_r > (6C_d + \sqrt{3}C_d)/6\}$.

In Proposition 3, we characterize the optimal reward rate offered by Medicare in four different regions of the range and the unit hospitalization costs (C_r, h_c). When the range and the unit hospitalization costs are in regions Ω_1 and Ω_2, we find that Medicare's total cost is an increasing function of the reward rate α in the range of α leading to a mobile clinic. Since the range cost C_r is relatively high compared to the unit hospitalization cost in regions Ω_1 and Ω_2, it turns out that the decline in the total hospitalization cost due to a higher reward rate is not enough to cover the rise in the cost savings shared with the provider. Hence, it is optimal for Medicare to choose a reward rate at which the provider offers a satellite clinic when $(C_r, h_c) \in \Omega_1 \cup \Omega_2$. Conversely, when the range and the unit hospitalization costs are in region Ω_4, we find that Medicare optimally chooses a reward rate at which the provider offers a mobile clinic. The range cost C_r is relatively low compared to the unit hospitalization cost in region Ω_4, and thus, Medicare's total cost is a decreasing function of the reward rate α in the range of α leading to a satellite clinic. Unlike the Ω_1, Ω_2, and Ω_4 regions, when $(C_r, h_c) \in \Omega_3$, Medicare's decision is more intricate. Namely, Medicare needs to compare two candidate reward rates: one minimizing the total cost in the range of α leading to a satellite clinic and the other one minimizing the total cost in the range of α leading to a mobile clinic. As Figure 5 illustrates, we also numerically observe that we can partition region Ω_3 into two sub-regions: Medicare chooses an optimal reward rate leading to a satellite clinic in one of these sub-regions, and the optimal reward rate motivates the provider to offer a mobile clinic range in the other sub-region.

Proposition 3 also characterizes the relationship between provider's profit and the four regions of (C_r, h_c). Except for region Ω_1 and a portion of region Ω_3, we find that the provider achieves a positive profit. In Ω_1 and a part of Ω_3, Medicare's total cost is an increasing function of the reward rate α regardless of the resulting modality due to the low unit hospitalization cost. Hence, Medicare chooses its optimal reward rate exactly at the level where the provider is indifferent between the status-quo and offering a satellite clinic.

Using the equilibrium outcomes presented in proposition 3, we can further analyze Medicare's optimal total cost, the optimal reward rate, and the provider's optimal profit with respect to the range and the unit hospitalization costs (C_r, h_c). Proposition 4 shows the effects of cost parameters on Medicare's total cost.

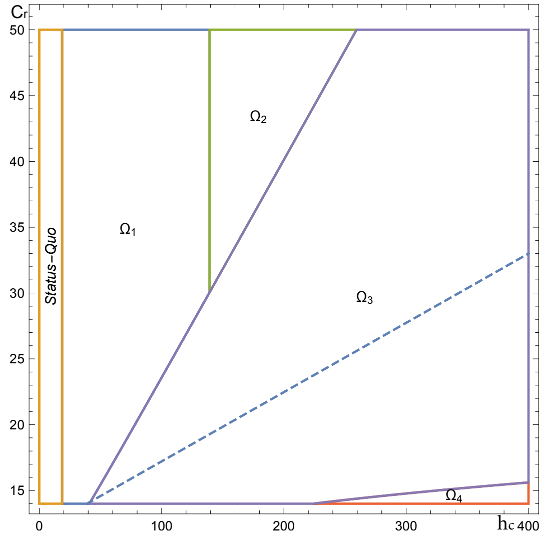
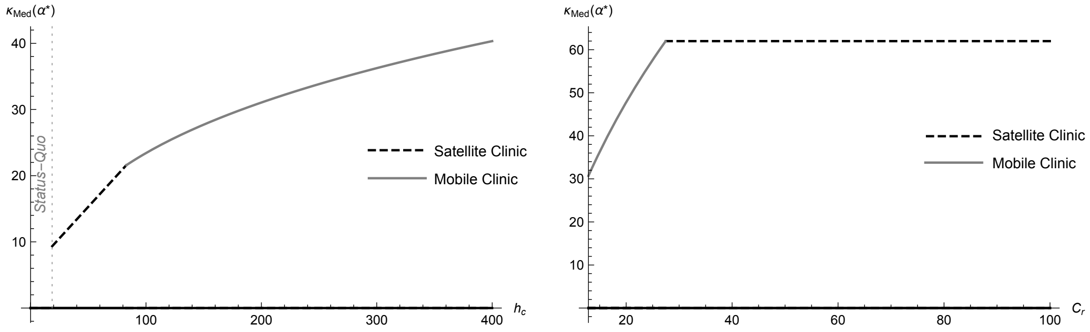


Figure 5. Optimal Solution Set as a function of h_c, C_r when $C_d = 10$

Proposition 4. *Medicare's optimal total cost is an increasing function of the unit hospitalization cost and a non-decreasing function of the unit range cost.*

Proposition 4 verifies that both (C_r, h_c) cost parameters adversely affect Medicare's optimal total cost. As we discussed in section 3.3.1, the provider decreases mobile clinic coverage as the range cost increases. Due to these changes, as the range cost increases, total hospitalization cost increases, and Medicare with a fixed reward rate faces higher costs. Note that the changes in the range cost do not affect the provider's decision when it offers a satellite clinic. In this case, Medicare's total cost does not change with higher range costs. However, with a fixed reward rate and higher h_c, the provider serves more patients with its new modality causing lower total hospitalization cost. This can help Medicare to save on hospitalization costs. Since Medicare's cost saving needs to be shared with the provider, for a fixed reward rate, as hospitalization cost increases, Medicare pays less total hospitalization cost and higher cost saving shared with the provider. For a range of reward rates, including α^*, higher total shared saving dominates the savings from lower hospitalization cost. Thus, Medicare's total cost is an increasing function of hospitalization cost. Figure 6 illustrates, Medicare's optimal total cost is increasing as h_c increases and as C_r is increasing Medicare's total cost is either increasing or constant.



a) $C_r = 15$ **b)** $h_c = 300$

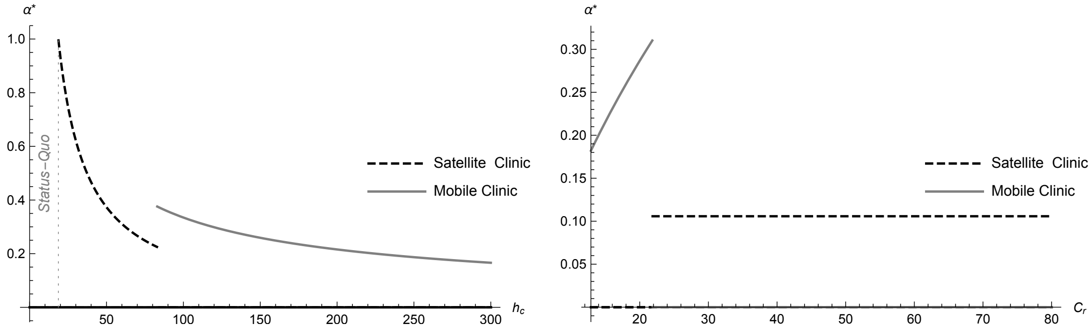
Figure 6. Medicare's optimal total cost $\kappa_{Med}(\alpha^*)$ as a function of h_c and C_r when $C_d = 10$.

Despite the somewhat apparent effects of the range and the hospitalization costs on Medicare's optimal total cost, the optimal reward rate and the provider's optimal profit have more intricate relationships with these cost parameters.

Proposition 5. *The optimal reward rate leading to a specific modality (i.e., satellite or mobile clinic) is a decreasing function of hospitalization cost and a non-decreasing function of range cost.*

From proposition 2, we know that Medicare's total hospitalization cost is monotonically decreasing in α and the cost savings shared with the provider is monotonically increasing in α. At the optimal level of α, the marginal benefits gained from lower hospitalization cost for Medicare equals the marginal loss in savings shared with the provider. A change in the unit hospitalization cost, or range cost, leads to an unbalanced trade-off between marginal total hospitalization cost and marginal cost savings shared with the provider. To be specific, as h_c increases, the marginal reduction in total hospitalization cost decreases, and the marginal cost savings shared with the provider increases. In this case, Medicare can decrease the reward rate to keep the balance between these two opposing marginal effects. Similarly, an increase in the range cost changes the balance in marginal costs by increasing the marginal effect of total hospitalization cost and decreasing the marginal effect of cost savings shared with the provider. Considering the fact that $\partial H(d_s^*, d_e^*)/\partial C_r > 0$ when the provider offers mobile clinic, Medicare can determine the balance between marginal total hospitalization cost and marginal cost savings shared with the provider by increasing the reward rate.

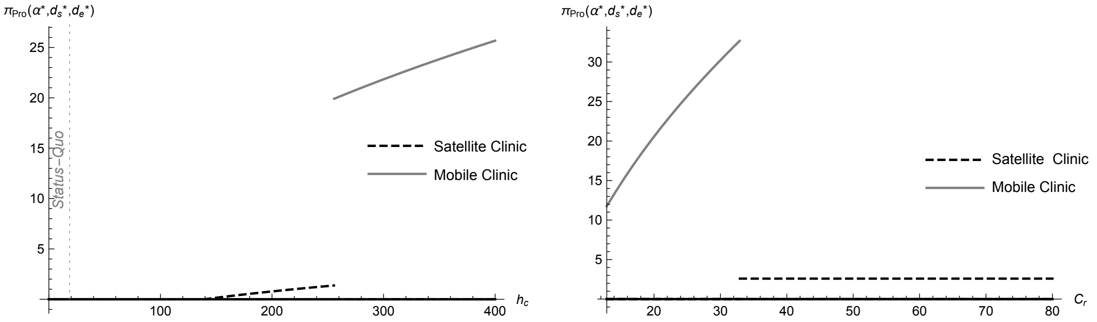
Through our numerical analysis, we find that Medicare optimally offers a lower reward rate as the unit hospitalization cost h_c increases. As we discuss in Section 3.3.1, for a fixed reward rate, the provider serves more patients via its new modality as the unit hospitalization cost increases. Since the total hospitalization cost directly depends on the fraction of patients served via the provider's new modality, the provider's response to changes in h_c may allow Medicare to reduce the optimal reward rate (α) after an increase in the unit hospitalization cost. As illustrated in Figure 7.a, such a decline in the optimal reward rate occurs unless the decrease in the unit hospitalization cost makes Medicare choose a reward rate that changes the new modality offered by the provider from a satellite clinic to a mobile clinic range. Since the provider needs a stronger motivation to offer a mobile clinic range, we observe a jump in the optimal reward rate once motivating the provider to offer a mobile clinic becomes optimal for Medicare. On the other hand, for a fixed reward rate, the provider serves less patients via its new modality as the range cost C_r increases. Since provider's response to changes in C_r already results in higher total hospitalization cost, reducing the reward rate would either increase the total hospitalization cost or make the provider offer a satellite clinic. As Figure 7.b illustrates, Medicare optimally offers a higher reward rate as the range cost C_r increases up to a threshold level. Once the range cost exceeds this threshold, Medicare finds it optimal to motivate the provider to offer a satellite clinic. As an increase in the range cost does not affect the optimal location of a satellite clinic, we observe that the range cost also does not affect Medicare's optimal reward decision once C_r exceeds the aforementioned threshold.



a) $C_r = 15$ **b)** $h_c = 200$

Figure 7. Optimal reward rate α^* as a function of h_c and C_r when $C_d = 10$.

As we discussed above, Medicare makes sharp changes in the optimal reward rate at the critical levels of the range, and the unit hospitalization cost illustrated. Consequently, these substantial adjustments in the optimal reward rate cause pronounced changes in the total hospitalization cost. Since Medicare is the party choosing the optimal reward rate, the sudden jumps or drops in the optimal reward rate do not lead to comparably extreme changes in Medicare's optimal total cost. However, they have notable implications for the provider's optimal profit. Namely, as illustrated in Figure 8, the provider's optimal profit rises sharply when the increase in the unit hospitalization cost makes the provider switch from a satellite clinic to a mobile clinic. Similarly, we observe a sharp decline in the provider's optimal profit when the increase in the range cost leads to a switch from a mobile clinic to a satellite clinic. Furthermore, Figure 8 also illustrates that any increases in the range and the unit hospitalization cost do not harm the provider's optimal profit as long as these changes in the cost parameters do not cause a switch between offering a satellite clinic and offering a mobile clinic.



a) $C_r = 25$ **b)** $h_c = 300$

Figure 8. The provider's optimal profit $\Pi^*_{Pro}(\alpha^*)$ as a function of h_c and C_r when $C_d = 10$.

3.4 Numerical Study

In this section, we illustrate that our key results characterizing the outcome of the interaction between Medicare and the provider continue to hold when we modify our original model. To this end, we perform a series of numerical studies by first modifying the distribution of the patient locations. We, then, consider an alternative cost function for operating a mobile dialysis service that applies a higher cost to modalities provided farther away from the main facility. Lastly, we develop a model allowing the provider to offer multiple new modalities simultaneously. Studying these alternative models particularly demonstrate the robustness of our findings in our original model regarding the effects of Medicare's reward rate (α) on the provider's decision to offer a new modality and Medicare's total cost.

3.4.1 Patients' distribution

In our original model, we consider a population of patients whose locations with respect to the clinic are uniformly spread out. Since dialysis clinics may be located after careful consideration of the patient population, it is reasonable to expect that the density of patients who are closer to the dialysis clinics is higher. According to the author's field study, some patients choose to relocate near a dialysis clinic after being diagnosed with end-stage renal disease. As per this reasoning, in the first extension of the model, we assume the following distribution of patients' locations with respect to the main clinic:

$$f(x) = -2\delta x + 1 + \delta \qquad 0 \leq x, \delta \leq 1 \tag{3.5}$$

Where $f(x)$ indicates the density of patients in the proximity of the main clinic, with higher δ indicating a greater density of patients in the proximity of the main clinic. This modification converts the H_0 and $H(d_s, d_e)$ to:

$$H_o' \equiv h_c \int_0^1 (-2\delta x + 1 + \delta) x dx = h_c(1/2 - \delta/6).$$

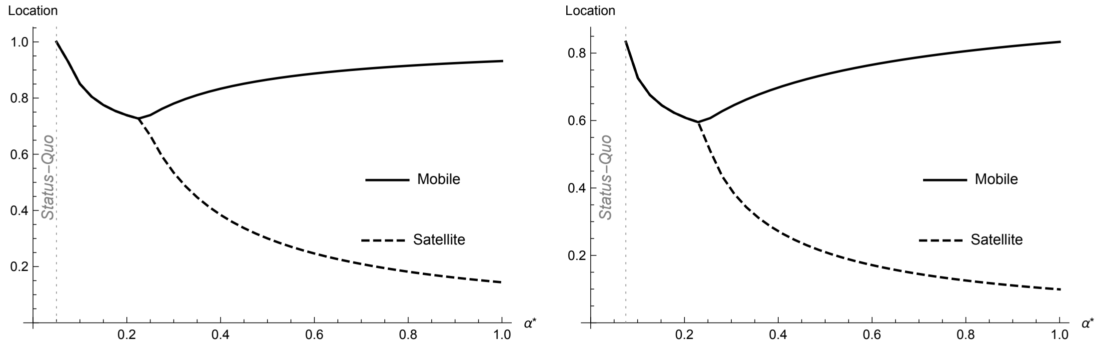
$$\begin{aligned} H'(d_s, d_e) \equiv & h_c(\int_0^{d_s/2} (-2\delta x + 1 + \delta) x dx \\ & + \int_{d_s/2}^{d_s} (d_s - x)(-2\delta x + 1 + \delta) dx + \int_{d_e}^{1} (x - d_e)(-2\delta x + 1 + \delta) dx) \end{aligned} \tag{3.6}$$

It is worth noting that the original model mentioned in section 3.2 is a special case of this new model. To be more precise, when $\delta = 0$ in equations 3.6 and 3.6, H_o' and $H'(d_s, d_e)$ equal H_o and $H(d_s, d_e)$ respectively. This new adjustment will alter the provider profit explained in equation 3.1 as well as Medicare's cost function indicated in equation 3.3, as they are both functions of H_o and $H(d_s, d_e)$.

We selected a low (0.2) and high (0.8) δ value for this numerical analysis to validate our main propositions. As previously stated, $\delta = 0.2$ denotes relatively small population congestion around the main clinic, whereas $\delta = 0.8$ denotes a predominantly centered patient population surrounding the main clinic.

The results of our numerical study demonstrate the robustness of our findings in proposition 1 to the changes in the distribution of patient locations. In particular, we find that with $\delta > 0$, the provider would hesitate to undertake the additional costs of a new modality for small values of the reward rate α, even if the mobile clinic range is optimally set. As a result, when α is small, the provider does not consider offering a new modality to be profitable. Offering a new modality becomes optimal when the reward rate improves sufficiently to cover the cost of the new modality. Specifically, when α rises, the provider begins by offering a satellite clinic. Once the incentive rate surpasses a threshold level, the provider optimally offers a $d_s^* < d_e^*$ mobile clinic range. In addition, we notice that when the incentive rate improves, the provider is able to support a greater number of patients through its new modality by relocating either its satellite clinic or the beginning points of its mobile clinic range closer to the main clinic.

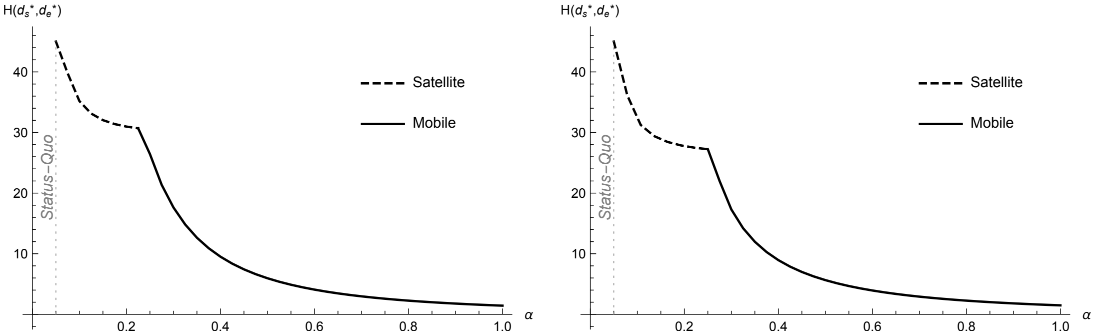
The placement of a satellite and a mobile clinic for a possible set of parameters is visualized in Figure 9. As the incentive rate improves, the provider expands the coverage of the new modality, similar to what we found in our original model.



a) $C_r = 20, C_d = 10, h_c = 100, \delta = 0.2$ **b)** $C_r = 20, C_d = 10, h_c = 100, \delta = 0.8$

Figure 9. d_S^*, d_e^* as a function of the reward rate (α) when $C_r = 20, C_d = 10, h_c = 100$ and $d_S^* = d_e^*$ if provider offers satellite clinic.

As explained in Proposition 2, the total hospitalization cost for Medicare drops with a higher reward rate. The revised cost structure discussed in this section follows the same pattern as figure 10 shows. The primary reason for this cost reduction is that the provider treats more patients through the new modality as the reward rate grows, as previously mentioned. The provider earns a greater overall incentive as a direct result of this cost decrease. As a result, when Medicare determines the appropriate reward rate, it must balance these two conflicting consequences of increasing the reward rate. Notably, as with the primary cost structure, hospitalization costs decrease at varying rates in Figure 10. The reduction rate varies according to the provider's range of mobile clinics or satellite clinics, and follows a piece-wise structure.

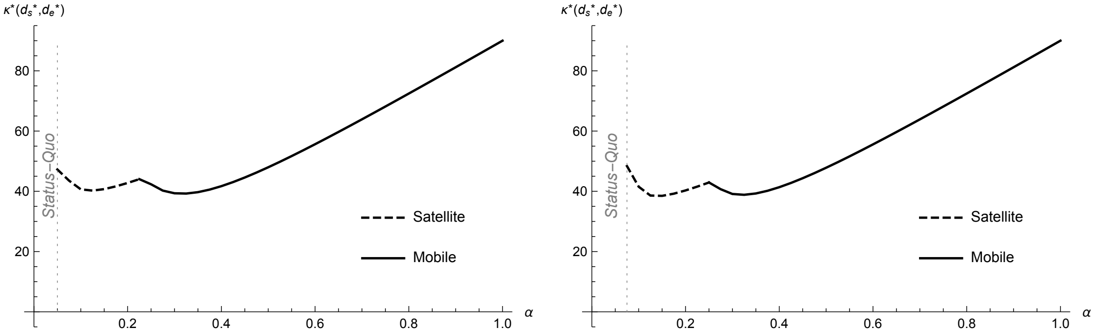


a) $C_r = 20, C_d = 10, h_c = 100, \delta = 0.2$ **b)** $C_r = 20, C_d = 10, h_c = 100, \delta = 0.8$

Figure 10. Medicare's hospitalization cost $H(d_S^*, d_e^*)$ as a function of the reward rate (α).

As previously noted, because hospitalization cost $H(d_s^*, d_e^*)$ is a piece-wise function, Medicare's total cost $\kappa_{Med}(\alpha)$ is similarly a piece-wise function of the reward rate α.

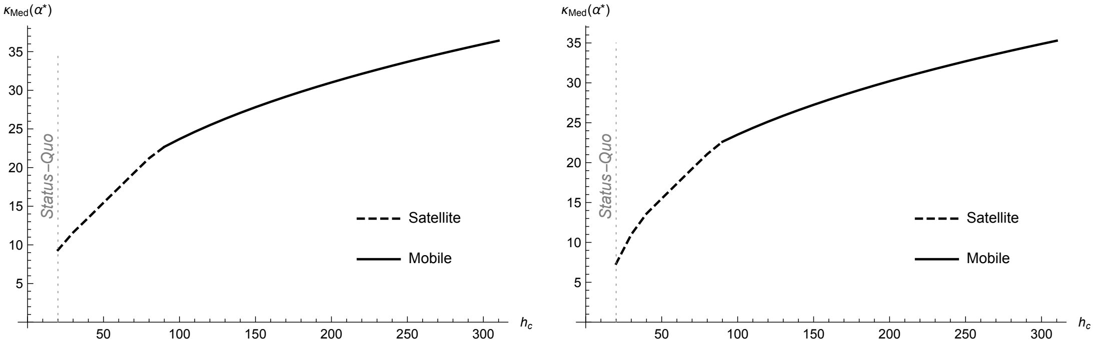
Figure 11 illustrates $\kappa_{Med}(\alpha)$ when $\delta \in \{0.2, 0.8\}$. In this case, the overall cost of Medicare is a function of two convex functions, one of which refers to the range of α leading to a satellite clinic and the other of which refers to the range of α leading to a mobile clinic, as previously reported. Medicare may need to identify two locally optimal reward rates and compare them in order to determine the optimal reward rate in this scenario since the total cost function of Medicare is not necessarily quasi-convex.



a) $C_r = 20, C_d = 10, h_c = 180, \delta = 0.2$ **b)** $C_r = 20, C_d = 10, h_c = 180, \delta = 0.8$

Figure 11. Medicare's total cost as a function of the reward rate (α).

The following step is to study the robustness of the findings of proposition 4 using different patient location distributions. To this end, we first examine how Medicare's optimal total cost responds to changes in unit hospitalization costs. With $\delta = 0.2$ and $\delta = 0.8$, we can see that Medicare's total cost is an increasing function of unit hospitalization cost, like in the case of $\delta = 0$. When the reward rate is fixed and h_c increases, the provider can serve a greater number of patients through its new modality, resulting in a reduced total hospitalization cost. This could result in savings for Medicare. Since Medicare must share its cost savings with the provider, as hospitalization costs rise, Medicare pays less total hospitalization costs and shares a larger portion of its cost savings with the provider. When the reward rate is optimal, the shared cost savings associated with decreased hospitalization costs outweigh the benefits associated with lower hospitalization cost resulting in higher total cost for Medicare. Figure 12 illustrates that Medicare's optimal total cost is increasing as h_c increases when $\delta \in \{0.2, 0.8\}$.

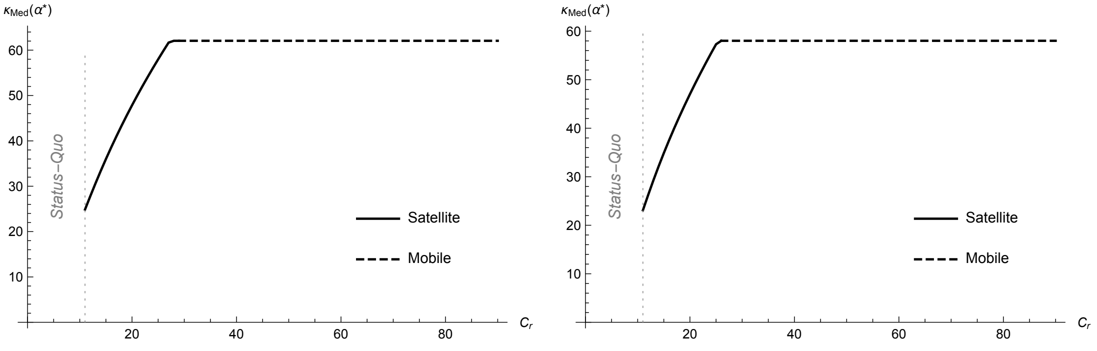


a) $C_r = 15, C_d = 10, \delta = 0.2$ **b)** $C_r = 15, C_d = 10, \delta = 0.8$

Figure 12. Medicare's optimal total cost $\kappa_{Med}(\alpha^*)$ as a function of h_c.

As with proposition 4, we demonstrate that as C_r increases, Medicare's total cost either increases or remains constant when the patient distribution is not uniform. This is due to the fact that the provider limits mobile clinic coverage as the range cost rises. With these modifications, as the range cost increases, the total hospitalization cost increases, and Medicare will incur increased expenses while the reward rate is fixed. It is important to note that changes in the range cost do not affect the provider's decision when offering satellite clinics. In this example, the total cost of Medicare remains constant as the range costs increase. The change in total medicare costs when C_r increases is displayed in figure 13.

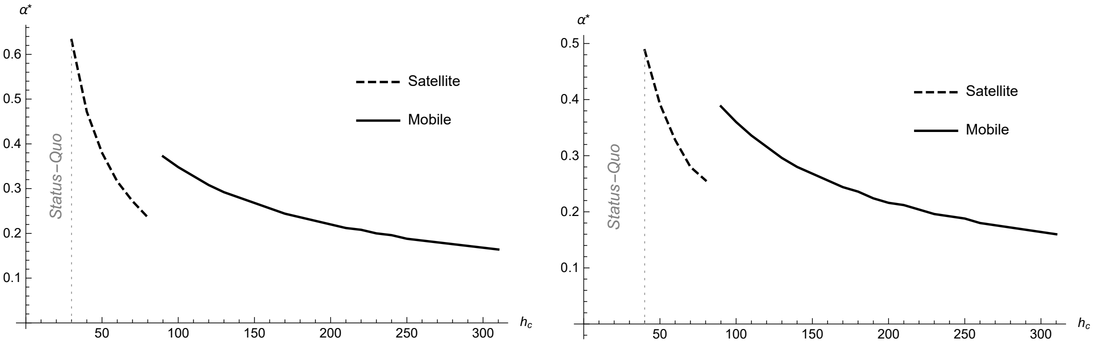
Our numerical analysis of different patient distributions also demonstrates that our qualitative insights about the sensitivity of the optimal reward rate offered by Medicare with respect to the unit hospitalization cost h_c continue to hold. When $\delta \in \{0.2, 0.8\}$, As illustrated in figure 14, when Medicare chooses a reward rate that shifts the provider's new modality from a satellite clinic to a mobile clinic range, the optimal reward rate increases since the provider needs



a) $h_c = 300, C_d = 10, \delta = 0.2$ **b)** $h_c = 300, C_d = 10, \delta = 0.8$

Figure 13. Medicare's optimal total cost $\kappa_{Med}(\alpha^*)$ as a function of C_r.

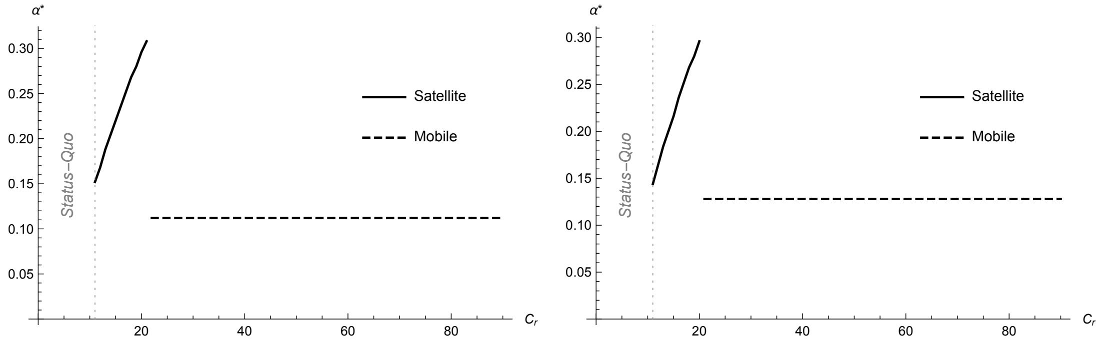
a higher incentive to offer a mobile clinic range. Otherwise, the optimal reward decreases as the unit cost of hospitalization increases. Like in our original model, the main driver of this result is that as the unit cost of hospitalization increases, the provider serves more patients via its new modality at a given reward rate. The provider response to changes in h_c may enable Medicare to reduce the reward rate when unit hospitalization cost increases, given that the overall cost of hospitalization is directly related to the proportion of patients served via the provider's new modality. This drop continues until the provider changes the modality being offered.



a) $C_r = 15, C_d = 10, \delta = 0.2$ **b)** $C_r = 15, C_d = 10, \delta = 0.8$

Figure 14. Optimal reward rate α^* as a function of h_c.

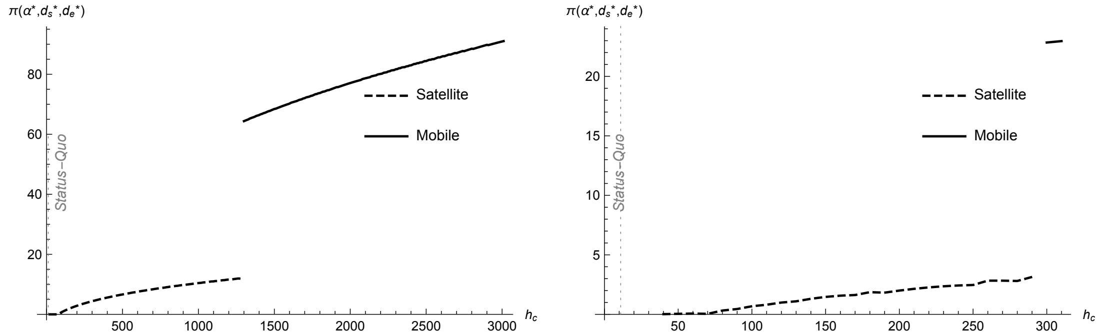
Additionally, we note that our results characterizing the relationship between the range cost and the optimal reward rate are also robust to the changes in the distribution of patient locations. As illustrated in figure 15, Medicare optimally offers a higher reward rate as the range cost C_r approaches a threshold value. Once the range cost reaches this threshold, Medicare determines that the satellite clinic is the most cost-effective option. As an increase in the range cost has no effect on the optimal location of a satellite clinic, we observe that after C_r exceeds the stated threshold, the range cost also has no effect on Medicare's optimal incentive decision. The structure of how the range cost affects the optimal reward remains unchanged after modifying the distribution of patient locations because, with $\delta > 0$, the provider's response to changes in C_r again results in a rise in overall hospitalization costs fixing the reward rate. Hence, decreasing the reward rate either increases total hospitalization costs or forces the provider to offer a satellite clinic.



a) $h_c = 200, C_d = 10, \delta = 0.2$ **b)** $h_c = 200, C_d = 10, \delta = 0.8$

Figure 15. Optimal reward rate α^* as a function of C_r.

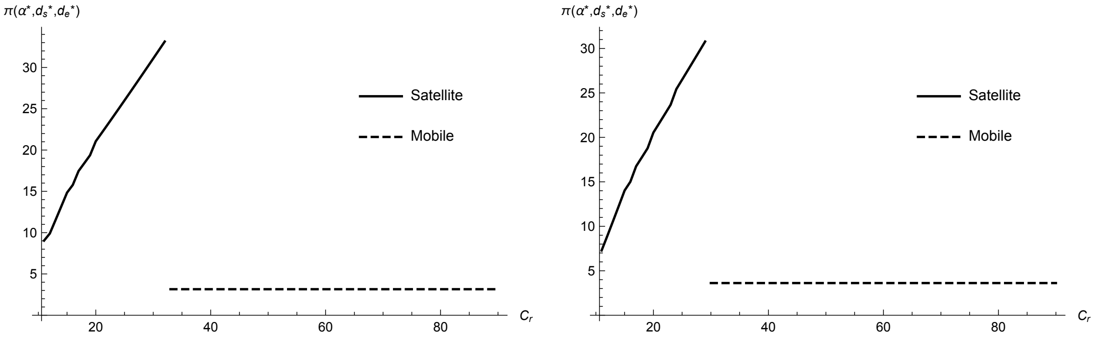
Furthermore, we examine the effect of patient distribution on the provider's profit. Figure 16 and 17 illustrate our numerical study's findings. As shown in Figure 16, provider profit increases as hospitalization cost increases, most notably when the provider switches from a satellite clinic to a mobile clinic.



a) $C_r = 25, C_d = 10, \delta = 0.2$ **b)** $C_r = 25, C_d = 10, \delta = 0.8$

Figure 16. The provider's optimal profit $\Pi^*_{Pro}(\alpha^*)$ as a function of h_c.

Additionally, when the range cost increases and the provider offers a mobile clinic, the pattern is identical to that observed in the main model. As illustrated in Figure 17, a significant drop in the provider's optimal profit is observed when the range cost increases, resulting in a switch from a mobile to a satellite clinic, for both examined distributions. We can conclude that all the key results hold when the patients' distance from the main dialysis clinic is not uniformly distributed.



a) $h_c = 300, C_d = 10, \delta = 0.2$ **b)** $h_c = 300, C_d = 10, \delta = 0.8$

Figure 17. Medicare's optimal total cost $\kappa_{Med}(\alpha^*)$ as a function of C_r.

3.4.2 Mobile Clinic Cost

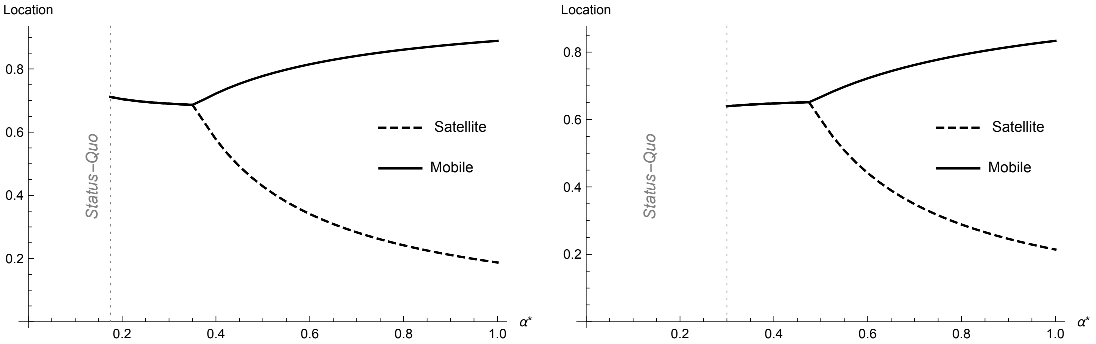
Following our analysis on patient distribution, we are now concentrating on the cost of operating a mobile clinic. In this section, a more complicated cost function for the new modality is examined. We realize, based on a review of the literature, that funding satellite clinics in remote places are more expensive [47]. As a result, we alter the cost of offering a new modality to equation 3.7. This has an effect on the provider's total cost.

$$C(d_s, d_e) \equiv C_r(d_e - d_s)(1 + \beta\frac{d_s + d_e}{2}) + C_d\frac{d_s}{2}(1 + \beta d_s) + C_d(1 - d_e)(1 + \beta d_e). \tag{3.7}$$

In the updated setting, $\beta = 0$ corresponds to the primary cost structure discussed in the original model. A larger β indicates the higher expenses of mobile or satellite clinic at a remote location. We replicate the analysis conducted in section 3.3.2 with the new cost structure when $\beta = 1$ & $\beta = 2$. The numerical analysis shows that all our key qualitative results remain true with the new cost structure. The remainder of this section discusses the major findings and observations from this numerical analysis.

Our numerical study demonstrates the validity of the conclusions in proposition 1. Even if the mobile clinic range is optimally selected, the provider would have little incentive to incur the additional costs associated with a new modality for low reward rates α. As a result, when α is low, the provider finds delivering a new modality unprofitable. Offering a new modality becomes optimal when the reward rate improves sufficiently to pay the expense of the new modality. More precisely, when α increases, the provider begins offering satellite clinic. Once the reward rate reaches a predetermined level, the provider offers the optimal range of $d_s^* < d_e^*$ mobile clinics. Additionally, we observe that as the incentive rate increases, the provider can support a greater number of patients via the new modality by relocating either the satellite clinic or the starting point of the mobile clinic range closer to the main clinic.

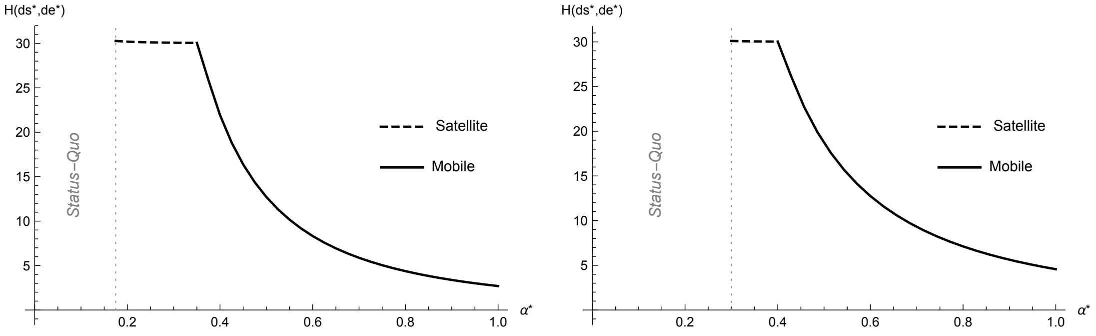
Figure 18 illustrates the location of a satellite and a mobile clinic for a hypothetical set of parameters. As the reward rate increases, the provider's coverage of the new modality expands, similar to what we saw in our initial model.



a) $C_r = 20, C_d = 10, h_c = 100, \beta = 1$ **b)** $C_r = 20, C_d = 10, h_c = 100, \beta = 2$

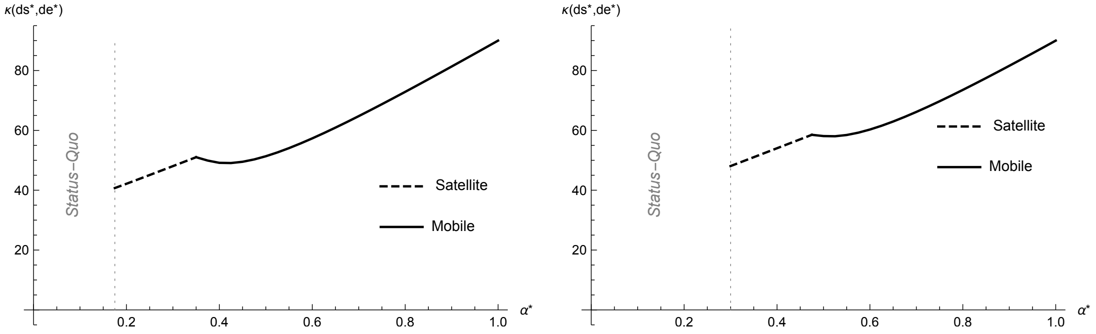
Figure 18. d_S^*, d_e^* as a function of the reward rate (α) when $C_r = 20, C_d = 10, h_c = 100$ and $d_S^* = d_e^*$ if provider offers satellite clinic.

As we establish in proposition 2, a greater reward rate reduces the total hospitalization cost for Medicare. The new cost structure introduced in this section follows the same pattern. Figure 19 illustrates Medicare's hospitalization cost as a function of reward rate. As previously stated, the fundamental reason for this cost reduction is that the provider serves more patients using the new modality as the reward rate increases. Notably, similar to our initial cost structure, Medicare's hospitalization costs fall at a variable rate in Figure 19. The reduction rate varies according to the provider's mobile or satellite clinics network and is structured in a piece-wise function. Furthermore, due to the piece-wise nature of the hospitalization cost function, Medicare's total cost is also a piece-wise function of the reward rate. Figure 20 depicts the relationship between κ_{Med} and reward rate with various different levels of β. Specifically, the overall cost of Medicare is a function of two convex functions, one of which corresponds to the range of α leading to a satellite clinic and the other of which corresponds to the range of α leading to a mobile clinic, as previously described.



a) $C_r = 20, C_d = 10, h_c = 100, \beta = 1$ **b)** $C_r = 20, C_d = 10, h_c = 100, \beta = 2$

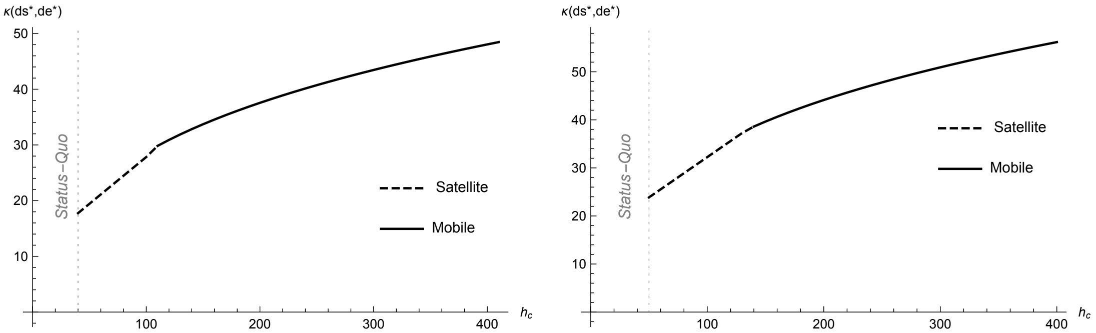
Figure 19. Medicare's hospitalization cost $H(d_S^*, d_e^*)$ as a function of the reward rate (α).



a) $C_r = 20, C_d = 10, h_c = 180, \beta = 1$ **b)** $C_r = 20, C_d = 10, h_c = 180, \beta = 2$

Figure 20. Medicare's total cost as a function of the reward rate (α).

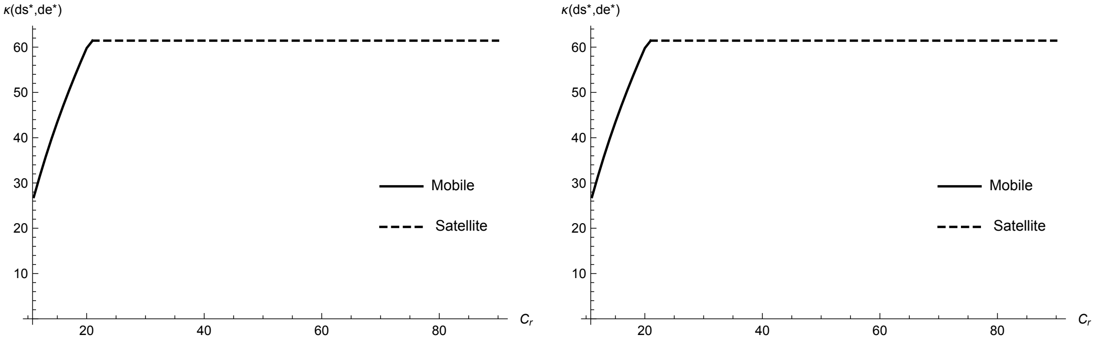
The conclusions of Proposition 4 are also tested with this new cost structure. When $\beta = 1$ and $\beta = 2$, the total cost of Medicare is increasing as the cost of unit hospitalization increases. With a fixed reward rate as h_c increases, a greater number of patients can be served by the provider's new modality, resulting in a lower total cost of care for the patient, which is comparable to what we saw in our original model. Since Medicare's cost savings must be shared with providers, as hospitalization cost increases, Medicare pays less in total hospitalization costs and more in cost savings shared with the provider. As a result, when the reward rate is optimal, the shared cost savings associated with lower hospitalization costs surpass the benefits associated with lower hospitalization costs, resulting in a higher total cost for Medicare. As illustrated in Figure 20, Medicare's optimal total cost is increasing in h_c when $\beta = 1$ and $\beta = 2$.



a) $C_r = 15, C_d = 10, \beta = 1$ **b)** $C_r = 15, C_d = 10, \beta = 2$

Figure 21. Medicare's optimal total cost $\kappa_{Med}(\alpha^*)$ as a function of h_c.

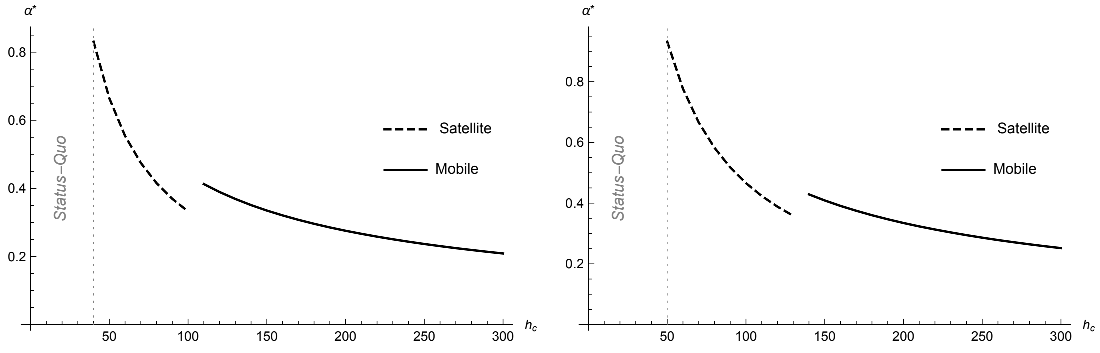
Next, similar to proposition 4, we illustrate how, as C_r increases, Medicare's overall cost either increases or remains constant under the new cost structure. This is owing to the fact that the provider reduces mobile clinic coverage when the range cost increases. With these changes, as the range cost rises, so will the total hospitalization cost, and Medicare will pay more costs while the reward rate is unchanged. It is critical to highlight that when a provider offers satellite clinics, changes in the range cost have no effect on the provider's decisions. Therefore, while the range costs increase, the total cost of Medicare remains constant in this scenario. Figure 22 illustrates the change in overall Medicare's costs as C_r increases.



a) $h_c = 300, C_d = 10, \beta = 1$ **b)** $h_c = 300, C_d = 10, \beta = 2$

Figure 22. Medicare's optimal total cost $\kappa_{Med}(\alpha^*)$ as a function of C_r.

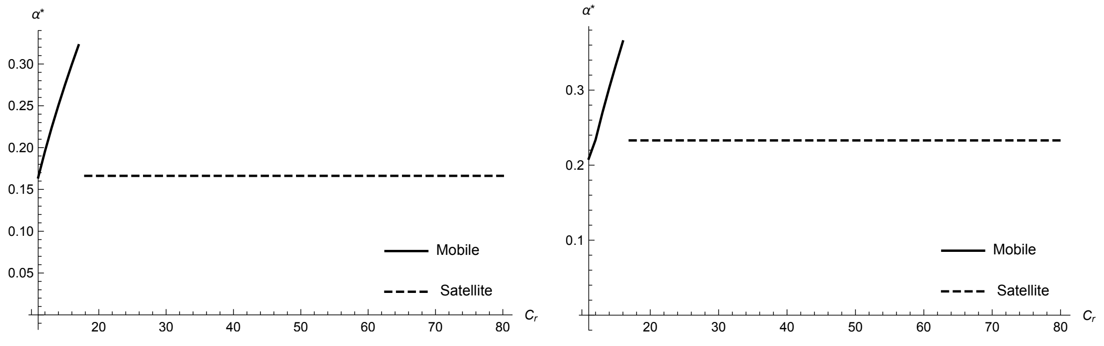
Using a new cost structure for offering a new modality, our numerical study demonstrates that when the unit hospitalization cost h_c rises, Medicare offers a lower reward rate. At a given reward rate, we know that if the unit hospitalization increases, the provider is willing to serve more patients through its newly developed modality. As a result of the provider's response to changes in h_c, Medicare may be able to reduce the reward rate when unit hospitalization costs increase since the overall cost of hospitalization is directly tied to the proportion of patients serviced by the new modality. This decrease in reward rate continues until the provider changes the modality. As seen in Figure 23, when Medicare selects a reward rate that switches the provider's new modality from a satellite clinic to a mobile clinic range, the optimal reward rate increases. In other scenarios, similar to what we observed in our original model, the optimal reward drops as the unit hospitalization cost increases.



a) $C_r = 15, C_d = 10, \beta = 1$ **b)** $C_r = 15, C_d = 10, \beta = 2$

Figure 23. Optimal reward rate α^* as a function of h_c.

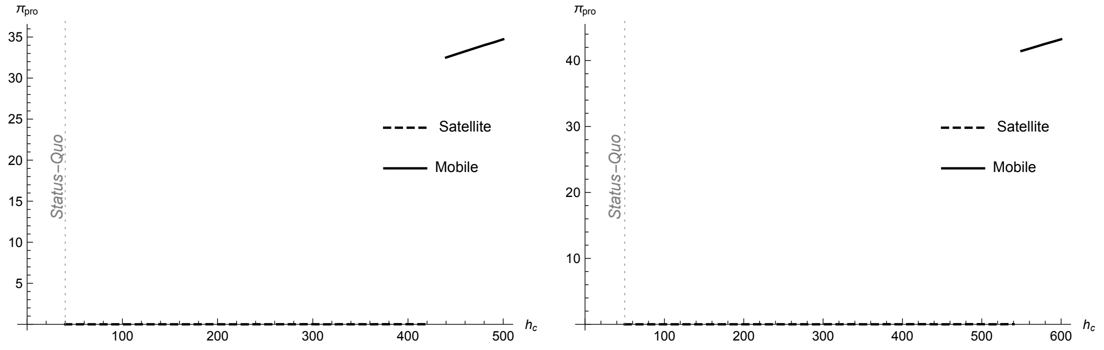
Similar to our findings under the initial cost structure, when the range cost increases as the provider offers mobile dialysis, the optimal reward rate increases in the unit range cost C_r after modifying the cost of operating a new modality. As the range cost C_r increases, the provider continues to serve fewer patients through the new modality with a fixed reward rate under the new cost structure. Hence, cutting the reward rate either further increases total hospitalization costs or pushes the provider to offer a satellite clinic, which both increase total hospitalization costs. The effects of the unit range cost on the optimal reward rate is demonstrated in Figure 24. Medicare offers a higher reward rate when the range cost C_r surpasses a specified threshold where Medicare finds the satellite clinic to be a more cost effective alternative. Due to the fact that an increase in the range cost has no effect on the ideal site of a satellite clinic, we notice once again that once C_r exceeds the indicated threshold, the range cost has no effect on Medicare's optimal option. This is consistent with the previous observation.



a) $h_c = 200, C_d = 10, \beta = 1$ **b)** $h_c = 200, C_d = 10, \beta = 2$

Figure 24. Optimal reward rate α^* as a function of C_r.

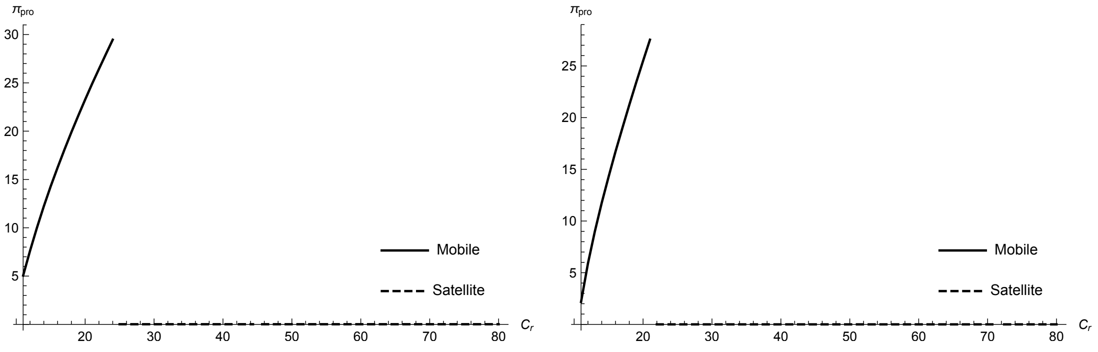
In addition, we investigate the impact of the new cost structure on the provider's profit margin. The conclusions of our numerical analysis are illustrated in the figures 25 and 26. The provider's profit increases with hospitalization cost, as illustrated in Figure25, and this is especially true when the healthcare provider shifts the modality from a satellite clinic to a mobile clinic.



a) $C_r = 25, C_d = 10, \beta = 1$ **b)** $C_r = 25, C_d = 10, \beta = 2$

Figure 25. The provider's optimal profit $\Pi^*_{Pro}(\alpha^*)$ as a function of h_c.

It is also found that the trend is identical to that observed in the main model when the range cost increases and the provider offers a mobile clinic. Increasing the range cost results in a considerable decrease in the provider's optimal profit when the provider switches the modality from mobile to satellite clinic, as seen in Figure 26. After considering all of the findings, we can conclude that all of the key results hold when the cost of delivering a new modality differs from the cost proposed in the main model.



a) $h_c = 300, C_d = 10, \beta = 1$ **b)** $h_c = 300, C_d = 10, \beta = 2$

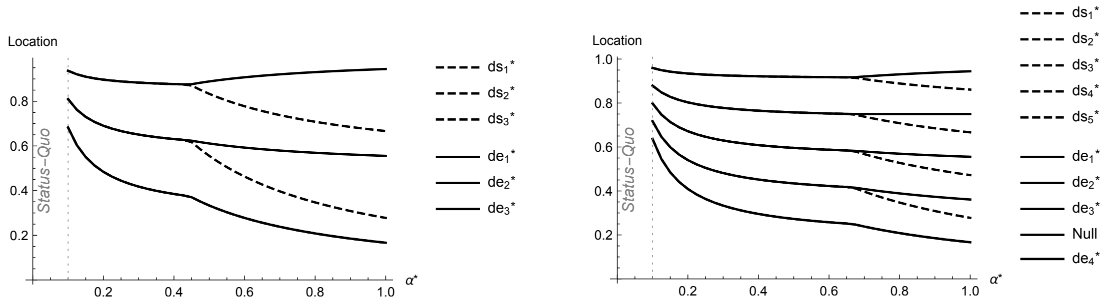
Figure 26. Medicare's optimal total cost $\kappa_{Med}(\alpha^*)$ as a function of C_r.

3.4.3 Multiple Mobile Clinics

In this section, we examine the possibility of providing multiple new modalities. We first consider the provider's ability to provide the new modality across three intervals, then extend our analysis to the case where five modalities are feasible. In both cases, we note that the provider offers satellite clinics for a wider range of reward rate. Nevertheless, all of the key insights obtained by studying the single modality model remain qualitatively unchanged.

Similar to our previous robustness studies, we first confirm that our findings in Proposition 1 continue to hold when the provider has the capability of operating multiple modalities simultaneously. We again find that with low reward rates, the provider would have little incentive to undertake further costs associated with new modalities. Optimal conditions for offering a new modality are reached when the reward rate improves sufficiently to pay for the new modalities. As the value of α rises, the provider begins to offer multiple satellite clinics. Once the reward rate has reached a specified threshold, the provider will provide the optimal range of mobile clinics. We also note that as the reward rate increases, the provider is able to service a bigger proportion of patients through the new modality. The location of a satellite and a mobile clinic with a hypothetical set of parameters is depicted in Figure 27. As illustrated in the basic model, coverage of a new modality increases as the reward rate increases.

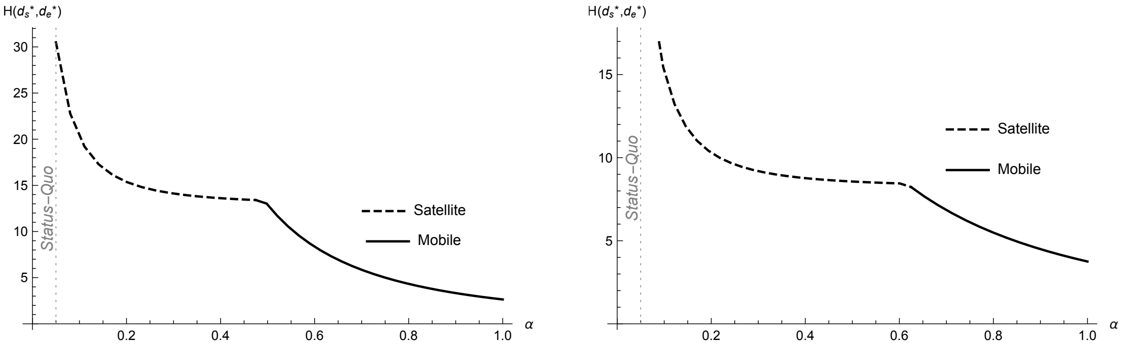
Next, we study the relationship between the reward rate, α, and Medicare's hospitalization cost. Our numerical study reveals that, as we prove in Proposition 2, the total cost



a) $C_r = 20, C_d = 10, h_c = 100$, 3 new modalities **b)** $C_r = 20, C_d = 10, h_c = 100$, 5 new modalities

Figure 27. Optimal location of new modalities as a function of the reward rate (α) when $C_r = 20, C_d = 10, h_c = 100$ and $d_{S_i^*} = d_{e_i^*}$ if provider offers satellite clinic.

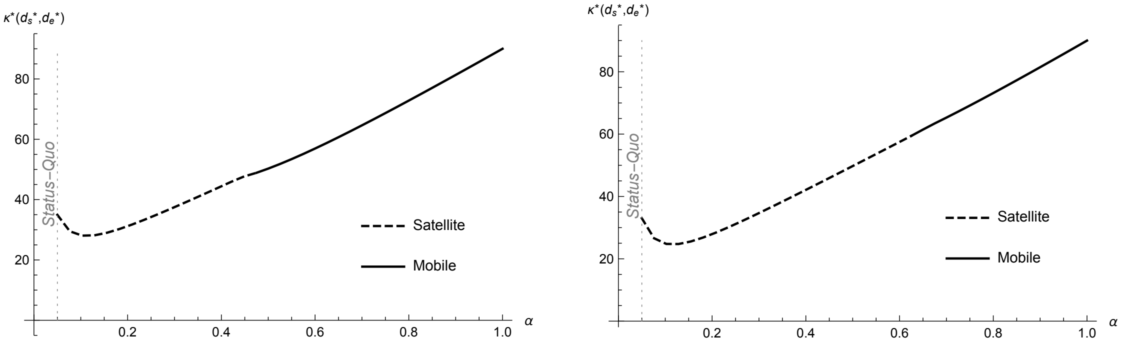
of hospitalization for Medicare decreases when the reward rate increases when multiple modalities are offered. The hospitalization cost for Medicare as a function of reward rate is depicted in Figure 28. As previously noted, the primary rationale for this cost reduction is that as the reward rate improves, the provider treats more patients using the new modalities, resulting in a fall in hospitalization costs. As a result of the provider's mobile or satellite clinics network, the decline rate is structured in a piece-wise format.



a) $C_r = 20, C_d = 10, h_c = 100$, 3 new modalities **b)** $C_r = 20, C_d = 10, h_c = 100$, 5 new modalities

Figure 28. Medicare's hospitalization cost as a function of the reward rate (α).

When multiple new modalities are introduced, the total cost of Medicare is also a piece-wise function of the reward rate because the cost of hospitalization is a piece-wise function. The relationship between κ_{Med} and reward rate with multiple modalities is depicted in Figure 29. As previously mentioned, the total cost of Medicare is a function of two convex functions, one of which relates to the range of α leading to multiple satellite clinics and the other of which corresponds to the range of α leading to multiple mobile clinics.

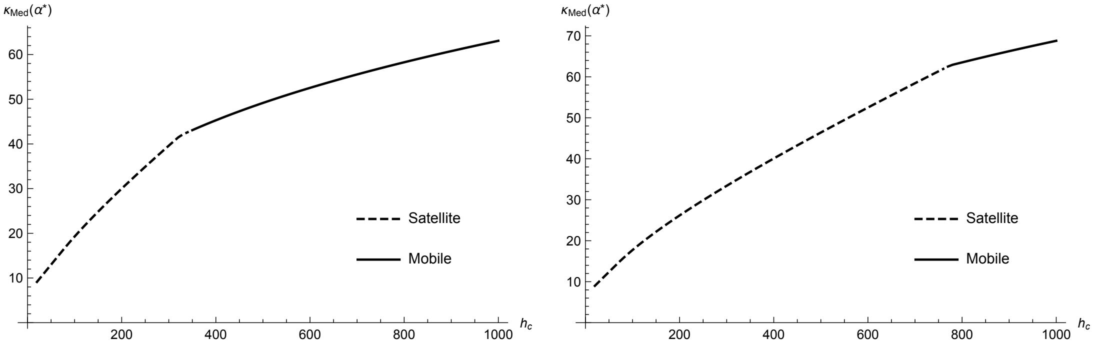


a) $C_r = 20, C_d = 10, h_c = 180$, 3 new modalities **b)** $C_r = 20, C_d = 10, h_c = 180$, 5 new modalities

Figure 29. Medicare's total cost as a function of the reward rate (α).

After examining Medicare's cost functions, we now turn our attention to verifying our results establishing the effects of cost parameters on Medicare's optimal total cost, which is presented in Proposition 4. Whenever the provider operates either three or five new modalities, the total cost of Medicare increases in the unit hospitalization cost. With a fixed reward rate as h_c increases, the provider's new modalities can serve a bigger proportion of patients, resulting in a lower total hospitalization cost that is comparable to the main model. Due to the fact that Medicare must share cost savings with providers, as hospitalization cost rise, Medicare pays less in overall hospitalization costs and more in cost savings shared with the provider, similar to the main model. At the optimal reward rate, due to the fact that the shared cost savings associated with lower hospitalization costs outweigh the benefits associated with reduced hospitalization costs, Medicare's optimal total cost is increasing in the unit hospitalization cost h_c when multiple modalities are offered, as illustrated in Figure 29.

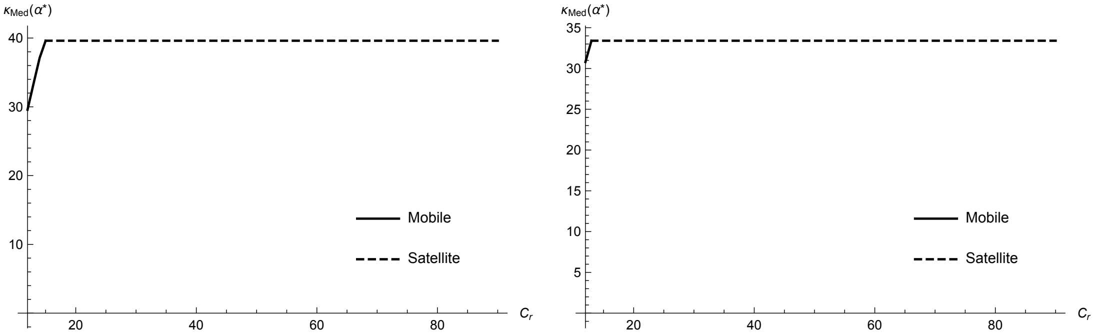
Furthermore, we confirm that Medicare's overall cost increases or stays the same when C_r increases when multiple modalities are offered. This is similar to our result presented in Proposition 4. Similar to our original model, the provider's coverage of mobile clinics is reduced when the range cost is higher. Hence, with these adjustments, as the range cost increases, the total hospitalization cost increases, and Medicare will pay higher costs with a fixed reward rate. When a provider offers satellite clinics, it is important to emphasize that changes in the range cost have no effect on the provider's decisions. As a result, even when the range cost increases, the



a) $C_r = 15, C_d = 10$, 3 new modalities **b)** $C_r = 15, C_d = 10$, 5 new modalities

Figure 30. Medicare's optimal total cost $\kappa_{Med}(\alpha^*)$ as a function of h_c.

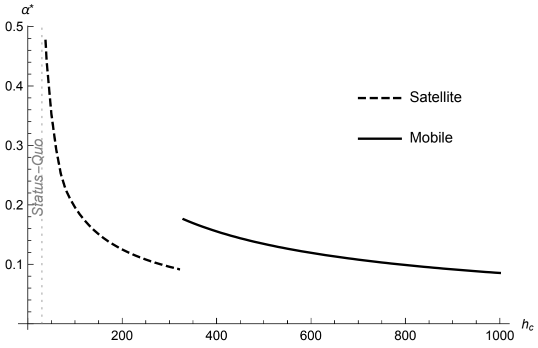
total cost of Medicare remains unchanged in this situation. Figure 31 depicts the changes in total Medicare cost as the value of C_r increases.



a) $h_c = 300, C_d = 10$, 3 new modalities **b)** $h_c = 300, C_d = 10$, 5 new modalities

Figure 31. Medicare's optimal total cost $\kappa_{Med}(\alpha^*)$ as a function of C_r.

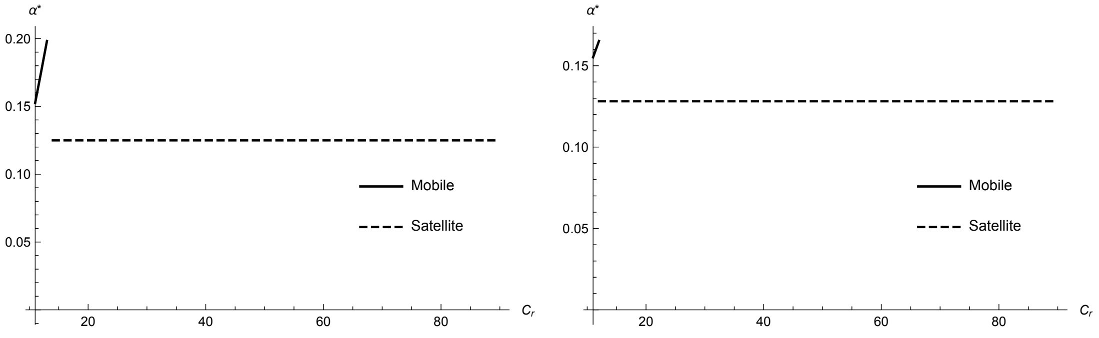
When a provider offers multiple modalities, our numerical study reveals that Medicare offers a lower reward rate as the unit hospitalization cost h_c increases. We know that if the unit hospitalization cost increases, the provider will serve more patients through its newly established modality if the reward rate remains constant. In response, Medicare may be able to cut the reward rate when unit hospitalization cost rises because the overall cost of hospitalization is directly related to the proportion of patients served by the provider. This decline in reward rate will exist until the provider changes the mode of dialysis delivery. As illustrated in Figure 32, the optimal reward rate increases when Medicare sets a reward rate that shifts the provider's new modality from a satellite clinic to a mobile clinic range.



a) $C_r = 15, C_d = 10$, 3 new modalities **b)** $C_r = 15, C_d = 10$, 5 new modalities

Figure 32. Optimal reward rate α^* as a function of h_c.

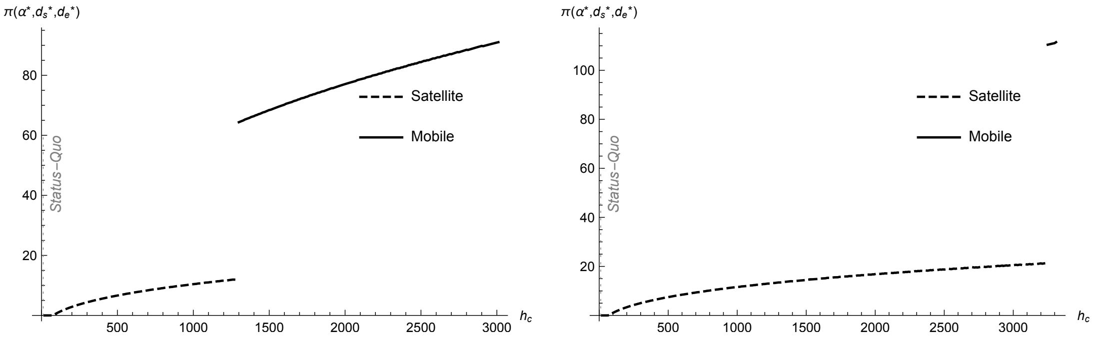
Similar to our original model, when a provider offers mobile dialysis, the optimal reward rate increases as the unit range cost C_r increases when multiple modalities are available. This is because the provider with a fixed reward rate treats fewer patients as the range cost C_r increases with the mobile clinic. Reduced reward rates may increase total hospitalization costs more or encourage providers to offer satellite clinics, both of which increase total hospitalization costs. Figure 33 illustrates the optimal reward rate. Medicare pays a higher reward rate when the range cost C_r exceeds a predetermined level where satellite clinic becomes the more cost effective choice. Because an increase in the range cost has no effect on the optimal location of satellite clinics, we see once again that once C_r surpasses the stated threshold, the range cost has no effect on Medicare's preferred alternative. This observation is compatible with the preceding one.



a) $h_c = 200, C_d = 10$, 3 new modalities **b)** $h_c = 200, C_d = 10$, 5 new modalities

Figure 33. Optimal reward rate α^* as a function of C_r.

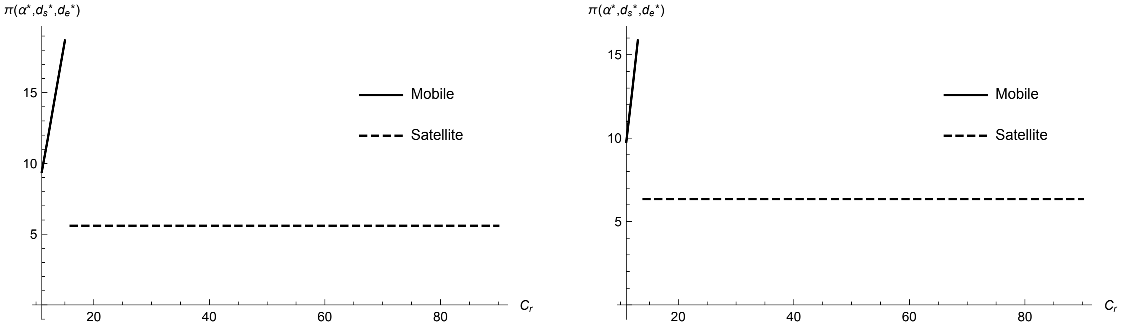
Finally, we analyze the influence of delivering a variety of new modalities on the profit margin of the dialysis provider. Figures 34 and 35 show the results of our numerical study, which are detailed in the text. The hospitalization cost, as shown in Figure 34, has a direct influence on the provider's profit. When the provider shifts the modality from a satellite clinic to a mobile clinic, her profit increase significantly.



a) $C_r = 25, C_d = 10$, 3 new modalities **b)** $C_r = 25, C_d = 10$, 5 new modalities

Figure 34. The provider's optimal profit $\Pi^*_{Pro}(\alpha^*)$ as a function of h_c.

Additionally, when the range cost increases and the provider offers a mobile clinic, the pattern is identical to that observed in our initial model. Increased range costs result in a significant fall in the provider's optimal profit when the provider switches from mobile to satellite clinic operation mode, as illustrated in Figure 35. After taking into account all of the data, we can conclude that when a provider offers multiple new modalities simultaneously, all of the important findings hold true.



a) $h_c = 300, C_d = 10$, 3 new modalities **b)** $h_c = 300, C_d = 10$, 5 new modalities

Figure 35. Medicare's optimal total cost $\kappa_{Med}(\alpha^*)$ as a function of C_r.

3.5 Summary and Conclusion

In this essay, the feasibility of incorporating mobile clinics as a new dialysis treatment has been investigated. In this study, we conduct a systematic examination of the relationship between new payment structures and providers' incentives to offer novel dialysis modalities. Using theoretical models, we demonstrate how Medicare should design the payment structure to reduce the patient's travel distance while minimizing Medicare's costs.

In this model, we examine a single provider who can offer dialysis via a mobile clinic. This innovative modality can treat patients from a single location, referred to as a satellite clinic, or over a range of locations wherein patient's within the range have zero travel, referred to as mobile dialysis.

Given that the provider incurs additional costs to implement this innovative modality, we propose that Medicare incentivize providers to facilitate this novel modality. We demonstrate that, under the model assumptions, a reimbursement mechanism exists that creates an incentive for the provider to offer a new modality in the form of mobile or satellite clinic. As an additional or exclusive service modality, a mobile or satellite clinic can be a win-win-win for Medicare, the dialysis provider, and the patients.

The incentive design used to compensate for the extra costs is a shared-savings mechanism in which Medicare shares a proportion of its hospitalization cost savings with the provider. We analytically prove that the provider finds it optimal to offer new modalities based on reimbursement rate under specific conditions and can increase its profit by offering new modality. Specifically, when hospitalization costs associated with travel distance are relatively high, the provider's profit can increase significantly by offering a new modality. We identify the conditions under which the provider offers the new modalities, as well as the proportion of patients who are served by the new modality.

This research is a first attempt to explore the possibility of introducing a new modality in the context of ESRD modality service design. We look at more sophisticated modeling setups in order to extend our model and ensure that the results are robust. First, we study an alternative option for patient distribution from the main clinic other than what was considered in the original model. This new distribution of patient locations enables consideration of increased density in the vicinity of the main clinic. Our numerical analysis of two alternative distributions indicates that the primary findings of the original model are valid even when patients' distance from main clinic follows a different distribution. Moreover, we study an alternative cost function for mobile dialysis clinic. This new modality cost structure considers a higher cost on modalities offered at a site remote from the clinic. In particular, we propose a nonlinear cost function for the provider of mobile or satellite clinics and conduct a numerical analysis using this new cost structure. We observe that all of the key conclusions from the original model are robust.

Finally, as the most important extension of this project, we design a model to analyze the possibility of offering multiple new modalities. We specifically aim at exploring how our findings carry over the cases wherein three and five modalities are offered. Our numerical study indicates that the provider's behavior is comparable to what we observed in the main model, with a few minor differences that do not affect the major findings.

A critical aspect of providing a new modality is determining the extent to which the new modality will be offered by dialysis care provider. Due to the fact that the nature of the new modality can vary greatly depending on whether mobile or satellite dialysis is offered, it is critical to analyze the features that the new modality should have and the extent to which the cost structures are comparable.

In the current work, we choose a simplified cost structure and incentive design to model provider and Medicare decision-making. This allows us to focus on critical research questions while still accounting for details such as patient coverage percentages. We believe that future research might build on our findings by adopting a more realistic pricing structure for satellite and mobile clinics that takes capacity constraints into account.

Although our findings on the introduction of new modalities and incentive designs are encouraging, additional research is needed to fully understand the scope of this new modality, particularly the capacity of mobile dialysis and the primary clinic, as well as the role of patients participating in this new modality. With a new setup, the following chapter examines a dialysis network that incorporates nurse-assisted home dialysis as an additional modality and considers patient preference when assigning patients to various modalities.

CHAPTER IV

A MATHEMATICAL MODEL FOR A PATIENT-CENTRIC DIALYSIS NETWORK

This work is coauthored with Prof. Nagesh Murthy and Dr. Eren Çil.

4.1 Introduction

Kidney transplant is the most cost-effective, and high-quality treatment option for kidney failure [48]. While the volume of kidney transplants has increased in recent years and data from 2019, indicate some encouraging trends, the demand for donor organs continues to exceed the supply [49]. As a result, the vast majority of patients with end-stage renal disease (ESRD) are treated with life-saving dialysis. The major portion of dialysis is administered in clinics, despite evidence that home-based hemodialysis (Home HD) may be more cost-effective [50, 51]. Home HD enables patients to maintain their social ties by preventing them from relocating to bigger cities and maintaining their cultural involvement, which is especially crucial for patients in rural areas and indigenous population [52].

Internationally, rates of home HD differ significantly; countries with a large home HD ”community,” such as New Zealand and Australia, sustain 18% and 9% of all dialysis patients on home HD. This compares to 3–6% in Canada [37]. In 2017, only 2% of hemodialysis patients in the U.S. were treated by home hemodialysis. Therefore, most patients must travel to the dialysis center, and the intensity of the treatment and transportation result in extensive fatigue, nausea, and other adverse effects [53]. The barriers that deter patients from selecting home HD include cognitive and physical barriers, lack of confidence, fear of social isolation, concerns about the insufficiency of treatment, and inadequate care and supervision [54, 55, 56, 57, 58]. In addition, phobia from dialysis equipment and needle are common obstacles to self-care home HD [56]. Other than the barriers we have mentioned before, another reason for the low participation rate might be the limited coverage of training cost for home HD to prepare patients [54].

In this study, we examine the feasibility of providing home HD with the assistance of a nurse practitioner. Home HD with nurse assistant is an alternate and appropriate care choice for patients who are not capable or willing to engage in self-care activities at home. Additionally, research comparing small assisted home HD programs to in-center HD for patients with physical and mental disabilities found that it is both safer and more cost efficient [59, 60]. Some countries such as Australia and New Zealand have developed innovative ideas to improve and maintain their high home HD rate. As an example, in southern New Zealand, trained nurses assist and support some home HD patients [52]. Recently, an assisted home HD pilot trial in Canada showed positive effects, and a broader study is now being undertaken to determine the cost effectiveness of this program [61]. The United States can leverage Australia, New Zealand, and Canada's policies, which may help overcome some of the challenges to home HD reported by patients.

As previously mentioned, dialysis places a significant financial burden on healthcare systems due to the resource-intensive nature of dialysis. The studies show that the annual cost of ESRD patients' transportation to and from dialysis units is expected to cost $3 billion where half of that is for ambulances [62]. On top of that, as mentioned in the first essay, increased travel for ESRD patients would result in increased hospitalization expenditures and could have an adverse impact on patients' health. The majority of patients who live in rural areas without access to dialysis clinics must move to larger cities. This clearly shows the disparities that exist in the US dialysis care system [63]. Thus, offering home HD with nurse assistance may result in decreased travel distance as well as significant improvement in patients' health outcomes and consequently decrease Medicare's cost, which is the focus of this study.

Medicare has attempted to facilitate home dialysis in the past by adjusting its payment policy. The ESRD Prospective Payment System, launched in 2011, established the same base payment for the home and in-center dialysis with an add-on payment per day for training. This reform was intended to provide an incentive for home-based therapies. However, these incentives had a minimal impact on promoting home HD. Patients, policymakers, and healthcare systems continually seek higher value, which can only be accomplished by genuine patient-centered creativity that encourages high-quality, high-value care. Significant steps are currently being taken to encourage the necessary transformative reforms. To remove the barriers of home HD, we propose that a professional caregiver (nurse) be present during the home HD session to carry out or support patients to do the dialysis. The involvement and support of the nurse during the dialysis decreases dialysis complications and improves patients' confidence in home HD as medical assistance is available if required. Home HD and assisted home HD cannot address all types of patients. Some patients can do the dialysis themselves, but they still prefer to go to clinics. We propose satellite clinics as a good alternative for this type of patient to minimize their traveling distance.

Some ESRD patients are willing to receive home HD. However, they are concerned about the dialysis complications and would like access to an on-call nurse who can answer their queries during dialysis sessions. This is particularly for stable patients, who may greatly benefit from the frequent use of telehealth. However, unstable patients who are struggling with travel schedules will still benefit from telehealth when there is no other option. Advances in modern telemedicine and telehealth technology have expanded the flexibility and usefulness of these technologies for patients who live far away from medical centers or finds it difficult to travel to a clinic. Telehealth and online patient supervision can be helpful in addressing regional obstacles to treatment, therefore improving access to home dialysis care, patient quality of life, and dialysis performance [64]. Telehealth and home dialysis also promote more home-based treatment, reduced travel time, and fewer visits to the clinic while still offering patient and care provider control and self-care. Telehealth and remote control of patients with dialysis have been increasing in the last decade, notably in Australia, where telehealth is extensively used for home dialysis patients. Remote surveillance has been shown to decrease hospitalizations and costs in high-risk hemodialysis patients [65, 66, 67]. Therefore, we suggest the use of telehealth for home HD as a new modality in the dialysis network for providers in the U.S.

The current COVID-19 pandemic has also contributed to the remarkable and rapid increase of the use of telemedicine in many areas of the world for healthcare, including in-center hemodialysis patients. Telehealth systems, particularly during the pandemic, assist in providing necessary treatment to patients while reducing the risk of contracting COVID-19 for both healthcare personnel (HCP) and patients. Despite being understudied to date, telehealth for hemodialysis patients has the potential to expand the adoption of home dialysis and raise patient care while ultimately lowering costs and enhancing results [53]. The lessons learned during the pandemic facilitate the healthcare delivery services in permanently incorporating telemedicine into their delivery systems. Post-COVID-19 healthcare delivery is unlikely to resemble the past years where healthcare delivery was centered around walk-in clinics and doctors' offices. The potential role of telehealth in medical care in the United States remains to be seen, especially in the context of the dialysis delivery network.

This chapter presents a comprehensive mathematical model that analyzes the provider's profit and Medicare's cost when multiple modes of modality are offered, including assisted home

HD. We propose that a nurse be present during the assisted home HD session, either physically or virtually via telemedicine, to administer dialysis or aid patients with dialysis. Furthermore, we suggest adding satellite clinics for the minority of patients who still prefer (or are required) to undergo dialysis in a clinic. The second essay's primary objective is to investigate the cost-effectiveness and feasibility of delivering home dialysis help to people currently on dialysis while also allowing for access to other main clinics and satellite clinics. We particularly focus on the following research questions:

-Whether, when, and how Medicare can incentivize dialysis service providers to introduce home dialysis service as a new modality to reduce hospitalization costs incurred by Medicare for ESRD patients on account of the detrimental impact of their recurring travel for in-clinic dialysis?

-What fraction of savings in Medicare's hospitalization cost on account of reduced patient travel due to new service modalities is needed to incentivize (i.e., compensate) the dialysis service provider to do so?

-How is this fraction of savings shared (i.e., reward rate) influenced by factors such as Medicare's cost structure, dialysis provider's cost structure, clinic's operating policy, geographic location of clinics and patients, and patient preference for in-clinic and home-dialysis?

This chapter is organized as follows; in section 4.2 we discuss the problem definition and the developed mathematical model. Next, we present the structure of our numerical study and some preliminary results.

4.2 Model setup

To remove the barriers of home HD, we investigate the feasibility of providing medical support to patients when they are on home dialysis. Assistance is delivered in two ways: nurses visit patients in their house or patients are connected to clinicians and nurses through telecommunications technology to increase the quality of their care and satisfaction. This ensures that nephrology consultations are available on a weekly basis, as prescribed by guidelines [64].

In the proposed dialysis distribution network, dialysis providers would offer dialysis services to patients through four distinct treatment modalities, $t \in T$, where $t = 1$ represents in-clinic dialysis under the direct supervision of healthcare providers, $t = 2$ represents satellite dialysis under the direct supervision of healthcare providers in a medical facility other than the main clinic, $t = 3$ indicates home dialysis administered to patients under the direct supervision of nurse in patients' house. $t = 4$ represents home dialysis performed by patients under the direct supervision of nurses via telemedicine.

We assume that the main clinic already exists and satellite clinics would operate if at least one patient is assigned to them. Therefore, the capital cost for the main clinic is based upon finished off and existing building and purchasing new machines. There is an extra capital cost, FC_s^2, for the satellite clinic due to remodeling the building and obtaining the permits. Typically, a dialysis center operates Monday to Saturday and serves patients in two schedules identified by $f \in F$ where $f = 1$ represent Monday, Wednesday, Friday and $f = 2$ represents Tuesday, Thursday, Saturday schedule.

S^t, $t \in T$ represents the set of dialysis service locations for treatment modality t. S^1 represents the main clinic location. S^2 is the set of possible locations for satellite clinics. S^3 identifies the set of locations from which nurses assigned to home dialysis depart and return at the end of the workday. S^4 represents the location from where nurses provide telemedicine service to patients.

We assume that patients are either uniformly or normally distributed around the main clinic and define a distance limit dt_p beyond which patients are unwilling to travel and hence expect home dialysis as per their preference for the nature of nurse assistance. Patient treatment costs CP_t including biomedical costs, and dialysis supplies vary according to dialysis service treatment. Usually, home dialysis biomedical costs are higher than those for main/satellite dialysis. Nurses who serve patients at home, work NT hours a day, and VNM identifies their annual salary. In-home nurses begin their travel to patients' homes from $s^3 \in S^3$ and return to the same location at the end of the day. They get a compensation of VT dollars per mile traveled and spend PT hours monitoring the dialysis procedure for each patient.

There are two types of nurses who serve patients at main/satellite clinics: a) registered nurse; b) patient care staff. Each registered nurse requires a minimum of 12 months of clinical nursing experience and an additional 6 months of clinical experience caring for patients with end-stage renal disease (ESRD), including experience with the hemodialysis procedure. The Centers for Medicare and Medicaid Services (CMS) mandates that one licensed nurse be on duty to supervise patient treatment for every twelve hemodialysis patients. Moreover, CMS requires that the dialysis center provide one patient care staff dedicated to dialysis care for every four patients [34]. The annual salary of registered nurse and patient care staff is defined as VN dollars and VP dollars in this model.

The network is designed for two shifts a day at the main and satellite clinics. We also assume five hours for in-clinic and satellite shift duration, with two schedules a week. We assume that the provider is compensated in proportion to the savings in hospitalization costs generated by the patient's reduced travel distance. The set, indices, and parameters are introduced in this section, followed by a discussion of the decision variables, and lastly, the math model is presented.

4.2.1 Sets, Indices and Parameters

Model sets, indices, and parameters are all listed in this section.

P= Set of patients' location

T= Set of modalities

F= Set of weekly schedules

S^t= Sets of locations where $t \in T$

p = Patient location index. $p \in P$

t = Modality index $t \in T = \{1, ..., 4\}$

f = Schedule index $f \in F = \{1, 2\}$

i, j= Location index. $i, j \in P \cup S^t | t = 3$

d_{ps^t} =Distance between patient's location p and s^t

dn_{ij} =Distance traveled by nurse from location i to j

dt = Distance threshold for patients' travel distance to main or satellite clinics

CP_t = Patient's treatment cost with modality t

TT_{ij} =Travel time between locations i and j

NT= Nurse available time in a day when serving home dialysis patients at home

PT= Service time needed for each patient for $t = 3$

CMC = Annualized cost of dialysis machine used in main and satellite clinics

CMH = Annualized cost of dialysis machine used in home dialysis

FCM= Annualized clinic construction/operation cost per unit of dialysis machine installed in main or satellite clinics

FC_{s^2}= Annualized fixed cost of starting a satellite clinic located at $s^2 \in S^2$

FC_{s^4}= Annualized fixed cost of offering telemedicine modality including nurse training, communication equipment, etc.

N_{S^t}= Number of Nurses needed in each shift of each schedule of modality S^t , $t = 1, 2, 4$

NP_{S^t}= Number of patient care staff needed in each shift of each schedule for modality S^t when $t \in \{1, 2\}$

VN= Annual cost for a nurse including salary and benefits when serving at $t = 1, 2, 4$. We assume that a nurse is working 40 hours a week. $N_{s^t} * 60$ provides us with total nurse hours needed to support two five-hour sessions in a day for 6 days a week. $N_{S^t} * 60/40$ number nurses FTE needed.

VP= Annual cost for patient-care staff including salary and benefits. We assume that a patient-care staff is working 40 hours a week. $NP_{s^t} * 60$ provides us with total patient-care staff hours needed to support two five-hour sessions in a day for 6 days a week. $NP_{S^t} * 60/40$ number of patient-care staff FTE needed.

VNM= Annual salary of a in-home dialysis nurse for working 40 hours a week. Assuming each day of schedule is limited to be 10 hours a schedule needs 30 hours hence each schedule requires 30/40=0.75 FTE of nurse.

VT= Variable travel cost for nurse when nurse is traveling, $ per mile for recurring travel in a year.

hc= Annual hospitalization cost incurred by Medicare per patient per mile of patient's recurring travel (3 trips a week and 52 weeks a year)

D_p= The distance between patient's location p and main clinic

α= Reward rate

PR_{ps^t}= Patients' preference parameter for modality t. This parameter takes value of 1 if patient p prefers modality t and zero otherwise. We assumed all patients are willing to receive dialysis at main and satellite clinics.

CS= Status quo cost for the provider where:

$$CS = |P| * CP_{t=1} + \lceil \tfrac{|P|}{4} \rceil (CMC + FCM) + \lceil \tfrac{|P|}{4*12} \rceil * (60/40) * VN + \lceil \tfrac{|P|}{4*4} \rceil * (60/40) * VP$$

4.2.2 Decision Variables

$$x_{ps^t} = \begin{cases} 1 & \text{If patient located at } p \text{ is assigned to modality } t \text{ located at } s^t \in S^t \\ 0 & \text{Otherwise} \end{cases}$$

$$y_{ijs^3f}=\begin{cases}1 & \text{If nurse located at } s^3 \text{ for home dialysis visits location } j \in P \cup s^3\\ & \text{after } i \in P \cup s^3 \text{ and } i \neq j \text{ in schedule } f\\ 0 & \text{Otherwise}\end{cases}$$

$$A_{s^2}=\begin{cases}1 & \text{If the satellite at location } s^2 \in S^2 \text{ is active}\\ 0 & \text{Otherwise}\end{cases}$$

$$B_{s^4}=\begin{cases}1 & \text{If the telemedicine modality is offered}\\ 0 & \text{Otherwise}\end{cases}$$

NMC_{s^t}= Auxiliary variable for number of machines needed at $s^t \in S^1 \cup S^2$

NMH= Auxiliary variable for number of machines needed for home dialysis.

SP_{is^3f}= Service start time of patient i if he/she is visited by nurse s^3 during shift f.

4.2.3 Math Model

The objective of the math model in this section is to maximize the provider's profit for any given fraction of the savings in hospitalization cost on account of reduced patient travel that Medicare is willing to share with the provider. The provider receives an extra payment proportional to the savings in patients' hospitalization costs when offering the new modalities. The cost of establishing a new dialysis distribution network covers the operating costs of active satellite clinics and telemedicine infrastructure, nurse and staff expenses, transportation costs for nurses serving patients at their homes, patients' treatment costs, dialysis equipment, and maintenance costs. The math model is presented as follows:

$$\text{Maximize } \alpha(hc(\sum_{p\in P} D_p - \sum_{t=1,2}\sum_{p\in P} x_{ps^t} d_{ps^t})) - [(\sum_{s_2\in S^2}(A_{s^2} * FC_{s^2}) + B_{s^4} * FC_{s^4})+$$

$$(VN * \sum_{t=1,2,4} N_{S^t} * 60/40) + (VP * \sum_{t=1,2} NP_{S^t} * 60/40) + (VNM * 0.75 * \sum_{s^3\in S^3}\sum_{j\in P}\sum_{f\in F} y_{s^3js^3f})+$$

$$(VT * \sum_{i\in s^3\cup P}\sum_{j\in s^3\cup P}\sum_{s^3\in S^3}\sum_{f\in F} y_{ijs^3f} dn_{ij}) + (\sum_{t\in T}\sum_{p\in P} x_{ps^t} CP_t)+$$

$$\sum_{s^t\in S^1\cup S^2}(CMC + FMC) * NMC_{s^t} + CMH * NMH - CS]$$

Constraint 4.1 ensures each patient is assigned to only one modality and served from only one location. This constraint is called traditional assignment constraint.

$$\sum_{t \in T} \sum_{s^t \in S^T} x_{ps^t} = 1 \qquad \forall p \in P \tag{4.1}$$

Constraint 4.2 ensures the distance travelled by patients who receive dialysis from main or satellite clinic is less than patients' predefined threshold. In other words, it guarantees that the model does not include any assignment that violates this threshold.

$$x_{ps^t} d_{ps^t} \leq dt \qquad \forall p \in P, s^t, t \in \{1, 2\} \tag{4.2}$$

Constraint 4.3 indicates if a nurse located at s^3 is assigned to serve a patient at location p for in-person home dialysis during the schedule f then location p should be on the nurse's route. To be more precise, this constraint ensures that there is just one variable that takes one if that patient is assigned to a nurse and that variable is always zero if that patient is not assigned to any nurse.

$$\sum_{j \in [P - \{p\}] \cup \{s^3\}} \sum_{f \in F} y_{pjs^3f} = x_{ps^3} \qquad \forall p \in P, s^3 \in S^3 \tag{4.3}$$

Constraint 4.4 ensures if nurse s^3 is assigned to serve patient p during schedule f, he/she will leave the patient's home to visit another patient or return to s^3. (in-flow/out-flow)

$$\sum_{i \in [P - \{p\}] \cup \{s^3\}} y_{ips^3f} = \sum_{j \in [P - \{p\}] \cup \{s^3\}} y_{pjs^3f} \qquad \forall f \in F, \forall s^3 \in S^3, \forall p \in P \tag{4.4}$$

Equation 4.5,4.6 make sure if a nurse located at s^3 is assigned to serve the patient at location p during shift f, she/he starts and finishes the route at s^3.

$$\sum_{j \in P} y_{s^3js^3f} \leq 1 \qquad \forall f \in F, \forall s^3 \in S^3, \tag{4.5}$$

$$\sum_{j \in P} y_{js^3s^3f} \leq 1 \qquad \forall f \in F, \forall s^3 \in S^3, \tag{4.6}$$

Constraint 4.7 ensures the time nurses spend traveling and serving patients is smaller than their shift length when they have to travel.

$$\sum_{i\in P\cup\{s^3\}}\sum_{j\in[P-\{i\}]\cup\{s^3\}} y_{ijs^3f}t_{ij} + (\sum_{i\in P\cup\{s^3\}}\sum_{j\in P\cup\{s^3\}} y_{ijs^3f} - 1)PT \leq NT \quad \forall s^3 \in S^3, f\in F, i \neq j \tag{4.7}$$

Constraint 4.8 specifies the time of service for a visited patient by a specific nurse based on the service time of the previous patient. This constraint determines the route based on the start times and locations of patients. It imposes strictly increasing service start times along the path of a nurse. This also prevents loops on a route, since returning to an already visited patient will violate the service start time constraint.

$$sp_{is^3f} + PT + t_{ij} \leq sp_{js^3f} + M(1 - y_{ijs^3f}) \qquad \forall s^3 \in S^3, f \in F, i \in P, j \in P \tag{4.8}$$

Constraint 4.9 ensures if a satellite serves a patient, then that satellite is active and its corresponding cost associated with the satellite is incurred in the objective function.

$$A_{s^2} \geq x_{ps^2} \qquad \forall p \in P, s^2 \in S^2 \tag{4.9}$$

Constraint 4.10 specifies that if a patient is assigned to telemedicine, the fixed cost associated with telemedicine is incurred in the objective function.

$$B_{s^4} \geq x_{ps^4} \qquad \forall p \in P, s^4 \in S^4 \tag{4.10}$$

Number of dialysis machines in clinic and home are calculated with constraint 4.11 assuming that there are two shifts in each day for each schedule.

$$\sum_{p\in P} x_{ps^t} \leq 4 * NMC_{s^t} \qquad \forall s^t \in S^1 \cup S^2 \tag{4.11}$$

Constraint 4.12 calculates the number of dialysis machines required to serve patients at home, which is exactly equal to the number of patients assigned to home HD with nurse assistance and telehealth.

$$\sum_{p\in P} x_{ps^t} = NMH \qquad \forall s^t \in S^3 \cup S^4 \tag{4.12}$$

Assuming that there are two shifts each day for each schedule, the total number of nurses for the clinic and satellite during each shift in each modality is calculated by constrains 4.13, 4.14

and 4.15. ($N_{S^t} * 60/40=$ number nurses FTE needed)

$$\frac{\sum_{p\in P} x_{ps^t}}{4} \leq 12 * N_{s^t} \qquad \forall s^t \in S^1 \cup S^2 \tag{4.13}$$

$$\frac{\sum_{p\in P} x_{ps^t}}{4} \leq 4 * NP_{s^t} \qquad \forall s^t \in S^1 \cup S^2 \tag{4.14}$$

$$\frac{\sum_{p\in P} \sum_{s^4\in S^4} x_{ps^4}}{4} \leq 12 * N_{s^4} \tag{4.15}$$

Constraint 4.16 ensures that patients' preference for home dialysis with nurse assistance is considered. To be more precise, this constraint ensures that there is no modality assignment against the patient's will.

$$\sum_{s^t} x_{ps^t} Pr_{ps^t} = 1 \qquad \forall p \in P \tag{4.16}$$

The decision variables' feasible values and non-negativity constraints are as follows:

$x_{ps^t} \in \{0,1\} \qquad \forall p \in P, \forall t \in T$

$y_{ijs^3f} \in \{0,1\} \qquad \forall i,j \in P \cup S^3, \forall s^3 \in S^3, \forall f \in F$

$A_{s^2} \in \{0,1\} \qquad \forall s^2 \in S^2$

$B_{s^4} \in \{0,1\} \qquad \forall s^4 \in S^4$

$sp_{js^3f} \geq 0 \qquad \forall i \in P, \forall s^3 \in S^3, \forall f \in F$

NMC_{s^t} & NMH are integer variables.

4.3 Numerical Analysis

This section outlines the details of our numerical study. To begin, we discuss the numerical analysis in further detail by introducing the parameters, variable factors, and their levels. Then, we'll explain the procedure for scenario construction and problem generation. The following section discusses the scenario analysis and highlights several of our observations and insights.

4.3.1 Scenario Development

It is worth mentioning that this study was motivated by a goal of evaluating the effect of several parameters on the optimal reward rate (i.e.,α^*), Medicare's Cost Saving Ratio ($MCSR$), and optimal modality assignment from the provider's perspective. As a result, we focus on quantifying the effect of changing the parameters and their interplay on performance measures. We classified the parameters into two categories. For each problem scenario, a set of parameters are fixed and do not change across the scenarios and different random draws. Table 1 displays the values of the fix parameters. The remaining parameters are referred to as "parameters of interest" (i.e., environmental factors), and they include the hospitalization cost (i.e.,hc), Geographic Distribution of Distance (i.e.,GDD), Distance Threshold (i.e.,DT), and Patient Preference for nurse assistance (PP). In order to have a general model and provide reliable insights, we set two values for factors of interest and came up with sixteen different scenarios (i.e. 2^4). Table 2 summarizes these parameter levels and their associated values. The remainder of this section outlines why the suggested values were chosen.

In 2018, the average annual Medicare spending for an ESRD case was $93,191 [70]. Hospitalization costs account for about 33% of ESRD expenditures [41]. At the low end, we can assume that 5% of the 33% annual hospitalization expense is derived from hospitalization costs, and at the high level, we assume that 10% of the annual hospitalization cost is derived from patient distance traveled. As a result, the low level value of annual hospitalization cost per patient is $\$93,191 * 0.33 * 0.05 \approx \$1538$, and the high level of hospitalization cost equals $\$93,191 * 0.33 * 0.1 \approx \$3075$. These numbers should be divided by seven which is the average number of miles that a patient travels on a one-way trip [43].

The median one-way driving distance to a dialysis clinic for remote hemodialysis patients is 10.4 miles [43]. To be consistent with our assumption in the first essay, we assume patient locations are uniformly distributed over (-30,30) for level I. Considering all hemodialysis patients, the median one-way travel distance to a dialysis center is 6 miles [43]. Thus, at level II, we can assume that the distance between patients' locations and the main clinic follows a bivariate normal distribution with the following parameters:

$$\mu = (0,0) \quad , \quad \Sigma = \begin{bmatrix} 15.68 & 0 \\ 0 & 15.68 \end{bmatrix}$$

For Patients Preference (PP), we choose the following two levels:

-When people do home dialysis 100% expect nurse at home.

-When people do home dialysis 80% expect nurse at home.

Table 1. Parameters' estimation

Parameter	Description	Amount	Reference
CP_t	The cost of a patient's treatment with a certain modality t	According to the data, the biomedical cost of clinic dialysis per treatment is \$115.2. Because there is no data on the biomedical cost of home dialysis, we took data from the Canadian payment system and used the same ratio for home treatment costs, calculating the biomedical cost of home dialysis as \$156.23.	[34]
NT	Nurse available time in a shift	10 hours; total hours for a schedule would be 30 hours hence we consider 1.5 * nurse salary for a 40 hour week	[34]
PT	Service time needed for each patient	4 hours per treatment	[34]
CMC	Annualized cost of dialysis machine used in clinic dialysis	\$1650 (The total cost of buying a machine is \$16500 which should be amortized in a straight-line manner over a 10-year period as per biomedical engineering staff recommendations.)	[34]
CMH	Annualized cost of dialysis machine used in home dialysis	\$3500 (The total cost of buying a machine is \$35000 which should be amortized in a straight-line manner over a 10-year period as per biomedical engineering staff recommendations.)	[68]
FCM ,FC_{s^2} ,FC_{s^4}	Fixed cost main clinic, Fixed cost satellite clinic located at $s^2 \in S^2$, Fixed cost telemedicine	Construction and operation cost per station for the center is estimated to be \$3500; and $FC_{s^2} = FC_{s^4}$= \$24000 (amortized over 10 years)	[34]
VN	Variable cost of nurse when nurse is not traveling. (Annual salary) Each shift is 5 hours	\$28 per hour. $VN = 28 * 40$ (hours per week)$*$1.35(benefits)$*$52 = 78624	[34]
VP	Variable cost of Patient-Care Staff who serve patient at main clinic and satellite clinics. (Annual salary)	\$15 per hour. $VP = 15 * 40 * 1.35 * 52 = 42120$	[34]
VNM	Variable cost of nurse (Salary per shift) We suppose that practitioner offers dialysis at home	\$28 per hour. $28 * 1.35 * 40 * 52 = 78624$	[34]
VT	variable travel cost for nurse when nurse is traveling (based on Canadian reimbursement policy \$0.53 per Kilometer)	0.53\$/Km*1.6 Km/mile*0.8 US\$*3*52 =105.83\$/mile	[69]

Table 2. Parameters' of interest

Parameter	Description	Level I	Level II
hc	Annual hospitalization cost incurred by Medicare per patient per mile of recurring travel (3 trips a week and 52 weeks a year)	\$219.7	\$439.3
GDD	Geographic distribution of patient location vis-a-vis main clinic	Uniform distribution over (-30,30)	Bivariate normal distribution $\mu = (0,0)$, $\Sigma = \begin{bmatrix} 15.68 & 0 \\ 0 & 15.68 \end{bmatrix}$
DT	Distance threshold	7.5 mile	15 mile
PP	Patient preference for an in-person nurse home dialysis vis-à-vis a tele-nurse	100% (home) - 0%	80% - 20%

In US home dialysis is being adopted by very small fraction of patients. Hence, we model offering of home dialysis either with nurse rostering or telemedicine as a way of patients getting comfortable with home dialysis during the early years of transition in US.

Table 3 describes all sixteen scenarios and the code associated with each scenario. L1 stands for Level I and L2 stands for Level II. For example, in scenario 16 (G2P2D2h2) all factors of interest get Level II values.

We consider 16 patients for this numerical analysis, and by generating 20 random problems for each combination in Table 3, we have 320 problems (i.e., $20 * 16$). To capture the effect of different incentives on the provider's decision and also on Medicare's total saving, we incrementally increase the reward rate by 0.05 from zero to 1, which creates 21 combinations. To be more precise, the total number of generated problems is 6720 (i.e.,$21 * 20 * 16$). We examine the cost of Medicare for each scenario and choose the one with the lowest value. The reward rate value associated with that cost is indicated by α^*. So, our analysis is based on the performance measures for the 320 selected problems.

Table 3. Scenario levels

Scenario#	Code	GDD	PP	DT	hc
1	G1P1D1h1	L1	L1	L1	L1
2	G1P1D1h2	L1	L1	L1	L2
3	G1P1D2h1	L1	L1	L2	L1
4	G1P1D2h2	L1	L1	L2	L2
5	G1P2D1h1	L1	L2	L1	L1
6	G1P2D1h2	L1	L2	L1	L2
7	G1P2D2h1	L1	L2	L2	L1
8	G1P2D2h2	L1	L2	L2	L2
9	G2P1D1h1	L2	L1	L1	L1
10	G2P1D1h2	L2	L1	L1	L2
11	G2P1D2h1	L2	L1	L2	L1
12	G2P1D2h2	L2	L1	L2	L2
13	G2P2D1h1	L2	L2	L1	L1
14	G2P2D1h2	L2	L2	L1	L2
15	G2P2D2h1	L2	L2	L2	L1
16	G2P2D2h2	L2	L2	L2	L2

4.3.2 Performance Metrics

In this essay we consider three key performance metrics to understand the implication of four environmental factors on Medicare's opportunity and ability to offer incentive to benefit from introduction of nurse assisted home-dialysis. We designed a suitable numerical study for a preliminary analysis. The first performance metric is the $\alpha *$ value, which determines the optimal reward rate at which Medicare's net cost is minimized. The second performance metric is the modality assignment, which defines the best combination of modalities to maximize the provider's profit and Medicare's cost saving in hospitalization costs. The third performance metric is the Medicare Cost Saving Ratio (MCSR) which compares Medicare's cost saving with the status-quo cost of Medicare.

We use CPLEX academic solver to solve the mixed-integer programming model and find the optimal solutions. All the above-mentioned scenarios are solved on a machine with an Intel® Core™ i7-6600U CPU @2.60GHz processor and 8GB RAM. Then, we record objective function values and optimal solutions and calculate the value of performance measures. Next, we present our preliminary insights from the scenarios discussed in this section and their associated optimal solutions.

Table 4. Optimal reward rate statistics

Scenario	Code	GDD	PP	DT	hc	Average	SD	LB	UB
1	G1P1D1h1	L1	L1	L1	L1	0.43	0.02	0.42	0.44
2	G1P1D1h2	L1	L1	L1	L2	0.23	0.02	0.22	0.24
3	G1P1D2h1	L1	L1	L2	L1	0.43	0.02	0.42	0.44
4	G1P1D2h2	L1	L1	L2	L2	0.23	0.02	0.22	0.24
5	G1P2D1h1	L1	L2	L1	L1	0.43	0.02	0.42	0.44
6	G1P2D1h2	L1	L2	L1	L2	0.23	0.02	0.22	0.24
7	G1P2D2h1	L1	L2	L2	L1	0.43	0.02	0.42	0.44
8	G1P2D2h2	L1	L2	L2	L2	0.23	0.02	0.22	0.24
9	G2P1D1h1	L2	L1	L1	L1	0	0	0	0
10	G2P1D1h2	L2	L1	L1	L2	0.43	0.44	0.24	0.63
11	G2P1D2h1	L2	L1	L2	L1	0.51	0.28	0.38	0.63
12	G2P1D2h2	L2	L1	L2	L2	0.73	0.32	0.59	0.87
13	G2P2D1h1	L2	L2	L1	L1	0	0	0	0
14	G2P2D1h2	L2	L2	L1	L2	0.43	0.44	0.24	0.63
15	G2P2D2h1	L2	L2	L2	L1	0.45	0.22	0.36	0.55
16	G2P2D2h2	L2	L2	L2	L2	0.93	0.07	0.9	0.96

4.3.3 Scenario Analysis for the optimal reward rate

In this part, we investigate the optimal reward rate obtained for each of the sixteen combinations and for each of the twenty randomly generated draws. As can be seen in Table 4, the average has a robust value almost in all cases in which the patients are distributed uniformly. For normally distributed patients, the average is approximately twice as high in instances where hospitalization cost is greater (0.43 vs 0.23). However, the average ranges from zero to 0.95 for the normally distributed patients. The other notable point in these types of problems is the zero value in scenarios 9 and 13. For both of these two scenarios, the distance threshold and hospitalization cost are at their lower level (i.e., Level I). This indicates that Medicare does not need to incentivize the provider by offering a fraction of the savings when there is a strict distance threshold in place from patients and the hospitalization cost is lower for Medicare. Finally, the highest observation belongs to 16th scenario where all of the factors of interest get the second level value and the 95% confidence interval is (0.9, 0.96). This scenario is a good example of a win-win-win for all parties involved in this problem, including Medicare, the provider and the patients. From Medicare's point of view, the hospitalization cost is lower and the majority of the savings should be invested to incentivize the provider to offer these new modalities. From the patients' point of view, they do not have to come back and forth between their home and the main clinic and they can be served by assisted home HD.

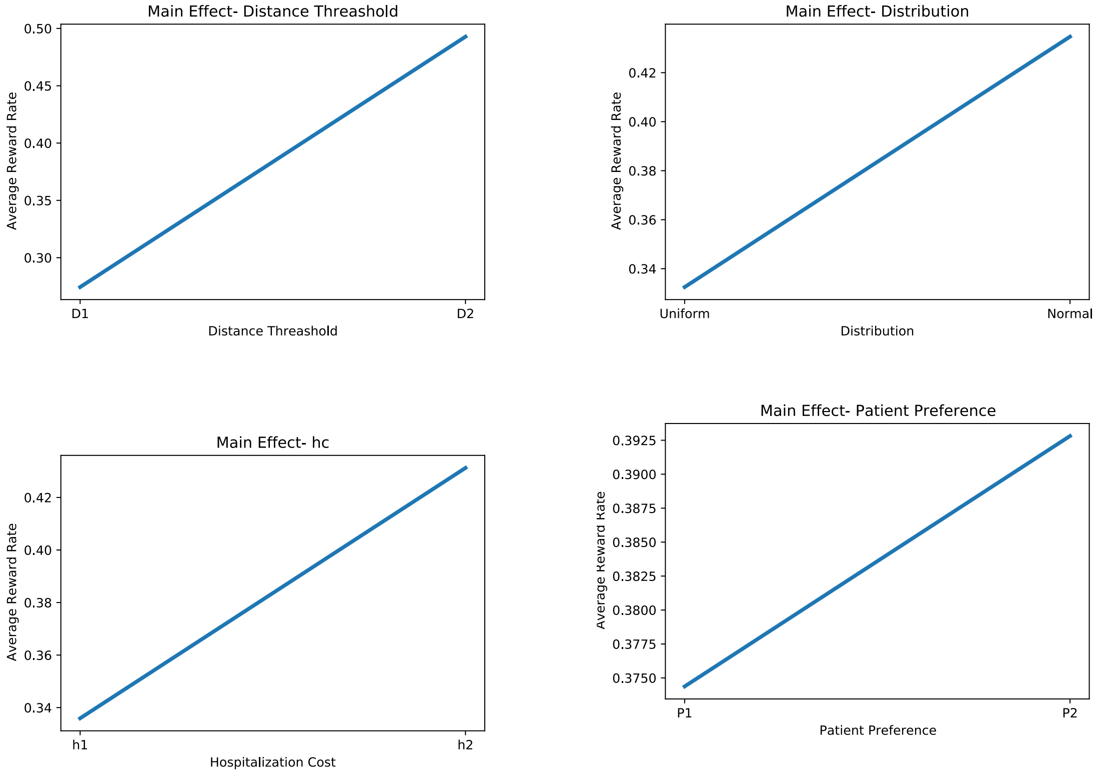


Figure 36. Main effects of GDD, HC, PP and DT on average reward rate

As illustrated in Figure 36, the average reward rate for all four environmental factors of interest increases as we progress from Level I to Level II. The highest slope belongs to distance threshold when we change it from 7.5 miles to 15 miles. To be more precise, Medicare should increase the incentive value by about 80%, from 0.274 to 0.493, when patients are less demanding.

4.3.4 Scenario Analysis based on Medicare Cost Saving

In this section, we analyze the value of the Medicare Cost Saving Ratio (MCSR) across all sixteen combinations and for all 20 randomly generated draws. As can be seen in Table 5, the average MCSR for uniformly distributed patients is about 23% higher in cases where hospitalization cost is higher (i.e., twice as much). It is worth mentioning that the MCSR for normally distributed patients is zero for four scenarios (scenario 9 , 11, 13 and 15) and close to zero (i.e., 2%) for the rest (scenario 10, 12, 14 and 16). The obtained values for MCSR within each scenario are consistent and the maximum difference we observed was 5%.

As we see in Figure 37, the patients' preference and distance threshold do not have any impact on MCSR. However, we can not make the same statement about unit hospitalization cost.

Table 5. Average MCSR for each scenario

Scenario#	Code	GDD	PP	DT	hc	MCSR
1	G1P1D1h1	L1	L1	L1	L1	0.32
2	G1P1D1h2	L1	L1	L1	L2	0.55
3	G1P1D2h1	L1	L1	L2	L1	0.32
4	G1P1D2h2	L1	L1	L2	L2	0.55
5	G1P2D1h1	L1	L2	L1	L1	0.32
6	G1P2D1h2	L1	L2	L1	L2	0.55
7	G1P2D2h1	L1	L2	L2	L1	0.32
8	G1P2D2h2	L1	L2	L2	L2	0.55
9	G2P1D1h1	L2	L1	L1	L1	0
10	G2P1D1h2	L2	L1	L1	L2	0.02
11	G2P1D2h1	L2	L1	L2	L1	0
12	G2P1D2h2	L2	L1	L2	L2	0.02
13	G2P2D1h1	L2	L2	L1	L1	0
14	G2P2D1h2	L2	L2	L1	L2	0.02
15	G2P2D2h1	L2	L2	L2	L1	0
16	G2P2D2h2	L2	L2	L2	L2	0.02

As we move from low hospitalization cost to high hospitalization cost, the cost saving ratio for Medicare has roughly doubled from 16% to 30%. This indicates that the benefit of offering new modalities at high hospitalization cost is higher and noticeable.

4.3.5 Scenario Analysis for Modality Assignment

In this section, we analyze the value of modality assignment for each predefined scenario and all 20 randomly generated draws. MPR, SPR, NPR and TPR stand for main clinic patients' ratio, satellite clinic patients' ratio, nurse assisted home HD patients' ratio, and telehealth patients' ratio, respectively. Table 6 summarizes the the proportion of patients assigned to each modality. As summarized in Table 6, patients are assigned to nurses to get assistance with dialysis in all cases with GDD at level I (i.e., scenarios 1 to 8) regardless of the hospitalization cost, distance threshold, and patients' preference. This indicates the significant impact of the geographic distribution of patients on results.

Furthermore, we can observe another trend in normally distributed patients. When the cost of hospitalization is low, as in scenarios 9, 11, 13, and 15, all patients are assigned to the main clinic, indicating that the new modalities are not cost effective for the provider. When patients are distributed normally and hospitalization costs are high at the same time (i.e., scenarios 10, 12, 14, and 16), we observe that patients are assigned to the main clinic and home assisted dialysis with nurse. This indicates that the high hospitalization cost does not

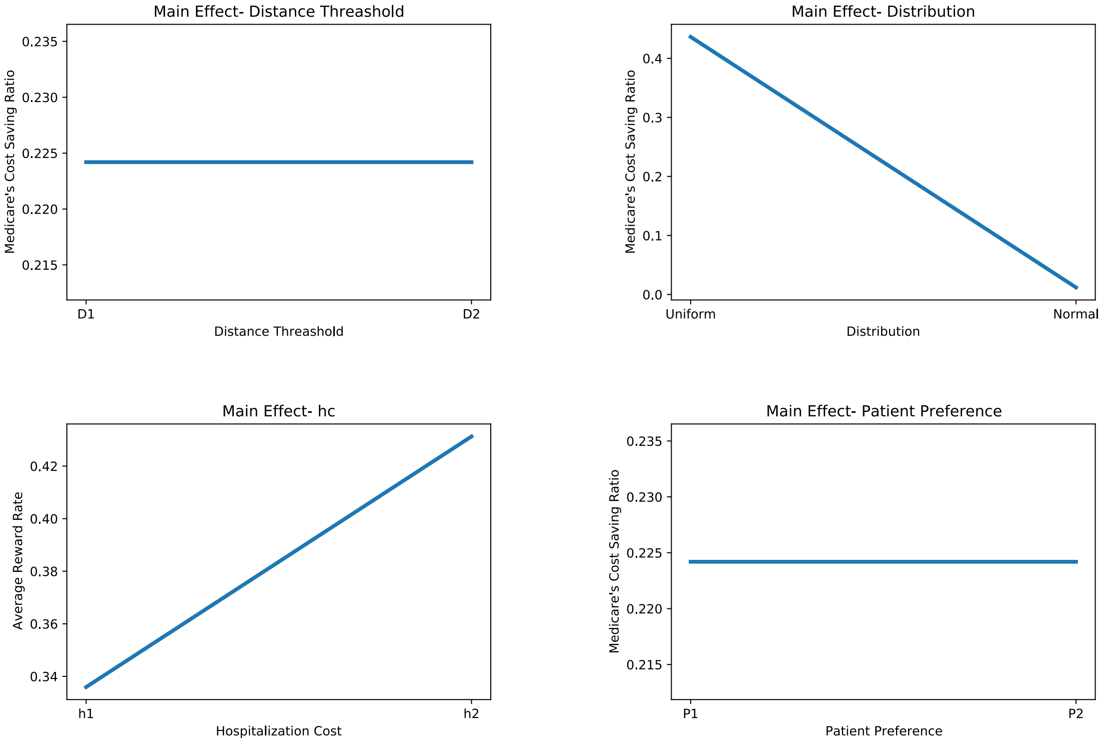


Figure 37. Main effects of GDD, HC, PP and DT on MCSR

Table 6. Average modality assignment ratios in all scenarios

Scenario#	Code	GDD	PP	DT	hc	MPR	SPR	NPR	TPR
1	G1P1D1h1	L1	L1	L1	L1	0	0	1	0
2	G1P1D1h2	L1	L1	L1	L2	0	0	1	0
3	G1P1D2h1	L1	L1	L2	L1	0	0	1	0
4	G1P1D2h2	L1	L1	L2	L2	0	0	1	0
5	G1P2D1h1	L1	L2	L1	L1	0	0	1	0
6	G1P2D1h2	L1	L2	L1	L2	0	0	1	0
7	G1P2D2h1	L1	L2	L2	L1	0	0	1	0
8	G1P2D2h2	L1	L2	L2	L2	0	0	1	0
9	G2P1D1h1	L2	L1	L1	L1	1	0	0	0
10	G2P1D1h2	L2	L1	L1	L2	0.5	0	0.5	0
11	G2P1D2h1	L2	L1	L2	L1	1	0	0	0
12	G2P1D2h2	L2	L1	L2	L2	0.5	0	0.5	0
13	G2P2D1h1	L2	L2	L1	L1	1	0	0	0
14	G2P2D1h2	L2	L2	L1	L2	0.5	0	0.5	0
15	G2P2D2h1	L2	L2	L2	L1	1	0	0	0
16	G2P2D2h2	L2	L2	L2	L2	0.5	0	0.5	0

always incentivize the provider; but the more important factor is the distance between the main clinic and the patient's residence. For instance, in scenario 10, the patient's assignment is evenly distributed between the main clinic and home assisted dialysis.

4.4 Summary and Conclusion

Multiple studies indicate the superiority of home HD compared to the traditional in-clinic dialysis [50]. However, the share of patients use home HD is very small and not comparable with in-clinic's share. There are different barriers that explain this issue. For example, unstable patients cannot do the home HD by themselves and they need to be under the control of professional medical staff. Other mentioned barriers include phobia from using dialysis equipment and needle on their own, fear of social isolation, lack of confidence, concerns about insufficiency of treatment and inadequate care and supervision. All of the mentioned obstacles are patient-oriented. However, other parties are involved in this small participation of patients. For example, some studies reported the limited resources of training cost for promoting home HD among patients. This indicates that the Medicare should find some innovative ways to incentivize the providers to offer and promote home HD and new modalities.

We propose different and innovative solutions to tackle the barriers to home HD. Assisted home HD is the first modality that is proposed in this study. This modality lifts some of these barriers for a fraction of patients, yet it is not enough. On top of that, we propose adding satellite clinics for those patients who are not willing to travel to the main clinic that is farther than their travel limit, particularly when nurse assisted HD is not offered to them. Finally, we offer a new modality which is called telehealth home HD. This modality is highly beneficial for those patients who are more confident in doing dialysis. This option is viable when their health status is stable and there is no recommendation against doing home HD by their nephrologist. Despite the fact that implementing all of the new modalities will increase the cost of healthcare, research indicates that less travel will result in a longer life expectancy and a lower risk of missing a dialysis session [18]. Previous research demonstrated the relationship between hospitalization cost and travel time. Hence, reducing travel time can result in a savings to Medicare's expenditure on ESRD patients.

To investigate the relationship between crucial factors affecting this complicated problem, we propose a mathematical model and a systematic approach for determining the importance of these factors. To begin with modeling practice, we ask some research questions to uncover all aspects of this problem. These questions include i) Whether, when, and how Medicare can incentivize dialysis service providers to introduce home dialysis service as a new modality to reduce hospitalization costs incurred by Medicare for ESRD patients on account of the detrimental impact of their recurring travel for in-clinic dialysis? ii) What fraction of savings in Medicare's hospitalization cost on account of reduced patient travel due to new service modalities is needed to incentivize (i.e., compensate) the dialysis service provider to do so? iii) How is this fraction of savings shared (i.e., reward rate) influenced by factors such as Medicare's cost structure, dialysis provider's cost structure, clinic's operating policy, geographic location of clinics and patients, and patient preference for in-clinic and home-dialysis? Thinking about these questions helped us to shape the mixed integer mathematical model with the objective function as a maximization problem and some constraints. Then, we proposed three performance measures, including optimal reward rate, Medicare's cost saving ratio, and modality assignment.

To quantify the effects of the investigated factor, we conducted a numerical analysis by classifying the parameters into two categories: factors of interest and fixed parameters. Then, we developed techniques for scenario development and problem generation in order to generate 6720 random problems.Then, we solved all of them to the optimal point and recorded the optimal value of the objective function and optimal solutions. Finally, we calculated the value of performance metrics.

Here we summarize the key findings of our study. Our numerical study shows that the average reward rate should be about 20% higher to incentivize providers in cases where patients are distributed uniformly and the hospitalization cost is high. Moreover, we found that there are even cases where offering the reward rate is not necessary by Medicare. On the other hand, there are some cases where Medicare should return almost all (around 96%) of its savings to provider to promote the new modalities. Furthermore, we show that as we move from level I to level II in all factors of interest, we see an increase in the average optimal reward rate. The highest increase happens for the distance threshold parameter. We observe that the average MCSR for uniformly distributed patients is about 23% higher in cases wherein that hospitalization cost is higher. Interestingly, the MCSR is zero for four out of eight scenarios in normally distributed patients. Our simulations indicated that the distance threshold and patient preference have no effect on MCSR and the MCSR's value is the same across level I and II for both of these two factors.

However, the higher hospitalization cost is around two times higher than the low hospitalization cost for Medicare.

Despite these innovative characteristics and contributions, this work contains modeling and methodological limitations that can be explored in future research. For example, in this study, we examine two distinct levels of patient choice. This assumption can be violated in practice due to the fact that we have a varying percentage of patients' preferences for certain modalities. Another exciting avenue for future research is to investigate the possibility of being allocated to many modalities on different days or weeks. However, this complicates the planning process for planners. It enables patients to experiment with many modalities in order to find the one they prefer. Another possibility is to examine the network's robustness to various sorts of disruption. From a methodological standpoint, the unpredictable nature of these factors requires novel modeling frameworks. Finally, we address problems on a small scale. However, when the size of the problem rises, the processing time increases exponentially, necessitating the development of new algorithms for dealing with large scale networks.

APPENDIX

TECHNICAL PROOFS – CHAPTER 3

Proof of Proposition 1: In this part, We first define the original constrained optimization problem for the provider, whose objective is to maximize the profit while subjecting to the span of mobile/satellite clinic.

$$\begin{aligned}\max \Pi_{Pro}(d_s, d_e; \alpha) &\equiv (\alpha[H_o - H(d_s, d_e)] - C(d_s, d_e))\\ &= \alpha(h_c/2 - h_c\frac{d_s^2 + 2(1-d_e)^2}{4}) - (C_r(d_e - d_s) + C_d(1 - d_e + d_s/2))\\ \text{Subject to} \quad & 0 \le d_s \le d_e \le 1\end{aligned}$$

This problem can be solved using Lagrangian multipliers. The Lagrangian function and the optimality conditions for this problem can be setup as follows:

$$\begin{aligned}&L = \Pi_{Pro}(d_s, d_e; \alpha) + \lambda_1(d_e - d_s) + \lambda_2 d_s + \lambda_3(1 - d_e)\\ &\frac{\partial L}{\partial d_s} = 0, \ \frac{\partial L}{\partial d_e} = 0,\\ &\lambda_1(d_e - d_s) = 0, \ \lambda_2 d_s = 0, \ \lambda_3(1 - d_e) = 0\end{aligned}$$

Solving the above system of equations, we determine seven potential optimal solutions to the provider's problem. Two of these candidate solutions are eliminated due to the non-negativity requirement for the Lagrange multipliers, i.e., $\lambda_i \ge 0$. We, then, establish under which condition each of the remaining five candidate solutions can be the unique optimal solution. In particular, we find that the provider offers mobile clinic to the entire population, with $d_s^* = 0$ and $d_e^* = 1$ when $C_r < C_d/2$. When the range cost is between $C_d/2 \le C_r < C_d$, the provider offers mobile clinic to cover the $[d_s^*, d_e^*]$ interval with $d_s^* = \frac{2C_r - C_d}{h_c\alpha}$ and $d_e^* = 1$. If $C_d \le C_r < (6C_d + \sqrt{3}C_d)/6$, the provider offers mobile clinic starting at $d_s^* = \frac{2C_r - C_d}{h_c\alpha}$ and ending at $d_e^* = 1 - \frac{C_r - C_d}{h_c\alpha}$. For higher range costs when $C_r > (6C_d + \sqrt{3}C_d)/6$, we observe the following response from the provider:

$$\begin{aligned}
\text{When} \quad & (\sqrt{3}/2 + 1)C_d/h_c < \alpha < \frac{3C_r - 2C_d}{h_c} \\
& d_s^* = d_e^* = \frac{2h_c\alpha + C_d}{3h_c\alpha} \\
\text{and when} \quad & \alpha > \frac{3C_r - 2C_d}{h_c} \\
& d_s^* = \frac{2(C_r - C_d)}{h_c\alpha}, d_e^* = \frac{h_c\alpha - C_r - C_d}{h_c\alpha}
\end{aligned}$$

Proof of Lemma 1: Following the examination of the provider's optimal response, we should ensure that the provider's profit is not negative in order to guarantee the provider's participation. As a result, we determined the lower bound of α for each interval of range cost by solving the following equation:

$$\Pi_{Pro}(d_s^*, d_e^*; \alpha) = 0 \tag{A.1}$$

For example, when $C_r < C_d/2$, we have that $\Pi_{Pro}(d_s^*, d_e^*; \alpha) = (\alpha h_c)/2 - C_r$, hence the lower bound of α becomes $2C_r/h_c$ in this case. Following a similar approach for the other interval of range cost, we establish the following lower bounds for α:

$$\begin{cases}
2C_r/h_c & \textit{if } C_r < C_d/2 \\
(\sqrt{-\frac{C_d^2}{2} + 2C_dC_r - C_r^2} + C_r)/h_c & \textit{if } C_d/2 \le C_r < C_d \\
(\sqrt{-\frac{3C_d^2}{2} + 4C_dC_r - 2C_r^2} + C_r)/h_c & \textit{if } C_d \le C_r < (6C_d + \sqrt{3}C_d)/6 \\
(\sqrt{3}/2 + 1)C_d/h_c & \textit{if } (6C_d + \sqrt{3}C_d)/6 \le C_r
\end{cases}$$

Proof of Proposition 2: After replacing the provider's best response in $H(d_s^*, d_e^*)$, we can take the first order condition of the function over α which yields

$$\frac{dH(d_s^*, d_e^*)}{d\alpha} = \frac{8C_dC_r - 3C_d^2 - 6C_r^2}{2h_c^2\alpha^3} \quad \text{When mobile clinic is offered} \tag{A.2}$$

$$\frac{dH(d_s^*, d_e^*)}{d\alpha} = \frac{-C_d^2}{6h_c^2\alpha^3} \quad \text{When satellite clinic is offered} \tag{A.3}$$

Since $C_r > C_d$, expression A.2 and A.3 are negative. Therefore, $H(d_s^*, d_e^*)$ is decreasing in α.

Proof of Proposition 3: After calculating the provider's optimal decision for d_s^* and d_e^*, we can determine the optimal reward rate for Medicare by solving the following equation:

$$\kappa^*_{Med} \equiv \min_{0\leq\alpha\leq 1} \kappa_{Med}(\alpha)$$

$$\text{where} \quad \kappa_{Med}(\alpha) = \begin{cases} \frac{1}{6}(2\alpha+1)h_c - \frac{(\alpha-1)C_d^2}{12\alpha^2 h_c} & \text{if } d_s^* = d_e^* \\ \frac{(-6C_r^2+8C_rC_d-3C_d^2)(\alpha-1)+2\alpha^3h_c^2}{4\alpha^2 h_c} & \text{if } d_s^* < d_e^* \end{cases} \tag{A.4}$$

Calculating the first derivative and checking the second derivative can assist us in determining the value of α^*. When $C_r > C_d$, Medicare's total cost is a piece-wise function of reward rate. As defined in the proposition, we categorize the solution space into four distinct zones. When $C_r, C_d, h_C \in \Omega_1$, Medicare determines that the optimal minimum reward rate is $\alpha_0 = \frac{\sqrt{3}C_d+2C_d}{2h_c}$ which incentivizes providers to offer satellite clinics and leaves provider with no profit due to it being a corner solution.

For higher hospitalization cost when $C_r, C_d, h_C \in \Omega_2$, Medicare offers

$$\alpha_1^* = \frac{1}{2}\left(\frac{\sqrt[3]{18C_d^2h_c^4+\sqrt{3}\sqrt{C_d^4h_c^6\left(C_d^2+108h_c^2\right)}}}{3^{2/3}h_c^2} - \frac{C_d^2}{\sqrt[3]{54C_d^2h_c^4+3\sqrt{3}\sqrt{C_d^4h_c^6\left(C_d^2+108h_c^2\right)}}}\right)$$

and provider operates a satellite clinic with a positive profit. Notably, when a provider offers a mobile clinic, the derivative of Medicare's cost function with respect to α equals to $\frac{6C_r^2-8C_rC_d+3C_d^2(\alpha-2)+2\alpha^3h_c^2}{4\alpha^3h_c}$ which is positive when $C_r, C_d, h_C \in \Omega_1 \cup \Omega_2$.

When $C_r, C_d, h_C \in \Omega_3$ Medicare must compare two local optimal solutions in order to determine the global minimum. One local optimal solution leads to a satellite, while the other leads to a mobile clinic. The optimal reward rate that results in satellite clinic is either α_0^* or α_1^*, while the optimal reward rate leading to mobile clinic equals to

$$\begin{aligned} \alpha_2^* \quad = \quad & \frac{\sqrt[3]{18h_c^4\left(6C_r^2-8C_rC_d+3C_d^2\right)+\sqrt{6}\sqrt{h_c^6\left(6C_r^2-8C_rC_d+3C_d^2\right)^2\left(6C_r^2-8C_rC_d+3C_d^2+54h_c^2\right)}}}{6^{2/3}h_c^2} \\ & + \frac{-6C_r^2+8C_rC_d-3C_d^2}{\sqrt[3]{108h_c^4\left(6C_r^2-8C_rC_d+3C_d^2\right)+6\sqrt{6}\sqrt{h_c^6\left(6C_r^2-8C_rC_d+3C_d^2\right)^2\left(6C_r^2-8C_rC_d+3C_d^2+54h_c^2\right)}}} \end{aligned}$$

When hospitalization cost is relatively high and $C_r, C_d, h_C \in \Omega_4$ Medicare optimally offers α_2^* and provider offers mobile clinic.

Proof of Propositions 4 and 5:

First we prove the reward rate is decreasing in h_c. If d_s^* and d_e^* are corner solutions and $d_s^* = d_e^*$, $\Pi_{Pro}(\alpha^*) = 0$

$$\frac{d\alpha^*}{dh_c}\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial \alpha} + \frac{\partial \Pi_{Pro}(\alpha^*)}{\partial h_c} = 0 \implies \frac{d\alpha^*}{dh_c} \equiv -\frac{\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial h_c}}{\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial \alpha}} \tag{A.5}$$

Where $\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial h_c} = \alpha^*(\frac{1}{6} + \frac{\partial H(\alpha^*)}{\partial h_c}) = \frac{\alpha^*}{h_c}(\frac{h_c}{2} - H(\alpha^*))$ and $\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial \alpha} = \frac{h_c}{6} + H(\alpha^*) + \alpha\frac{\partial H(\alpha)}{\partial \alpha} = \frac{h_c}{2} - H(\alpha^*)$ as $\frac{\partial H(\alpha^*)}{\partial h_c} = \frac{1}{3} - \frac{H(\alpha^*)}{h_c}$ and $\frac{\partial H(\alpha)}{\partial \alpha} = \frac{2(\frac{h_c}{2} - H(\alpha^*))}{\alpha}$. Therefore, from equation A.5, the reward rate is decreasing in h_c since $\frac{d\alpha^*}{dh_c} = -\frac{\alpha}{h_c} < 0$.

We know the provider's best response is not sensitive to C_r when satellite clinic is offered. Therefore, $\frac{d\kappa^*_{Med}}{dC_r} = 0$ when satellite clinic is offered. Now we prove that Medicare's cost is increasing in C_r when optimal reward rate is an interior solution. Taking derivative of Medicare's cost function with respect to C_r results in

$$\frac{d\kappa^*_{Med}}{dC_r} \equiv \frac{\partial \kappa_{Med}(\alpha^*)}{\partial \alpha}\frac{\partial \alpha}{\partial C_r} + \frac{\partial \kappa_{Med}(\alpha^*)}{\partial C_r} \tag{A.6}$$

Medicare chooses the optimal reward rate that minimizes equation 3.3; therefore, $\frac{\partial \kappa_{Med}(\alpha^*)}{\partial \alpha} = 0$, and we can rewrite equation A.6 as:

$$\frac{d\kappa^*_{Med}}{dC_r} = (1 - \alpha^*)\frac{\partial H(d^*_s, d^*_e)}{\partial C_r} \tag{A.7}$$

Where $0 < \alpha^* < 1$ and $\partial H(d^*_s, d^*_e)/\partial C_r = \frac{3C_r - 2C_d}{h_c \alpha^2}$. Assuming $C_r > C_d$, from equation A.6 and A.7 we can conclude $\frac{d\kappa^*_{Med}}{dC_r} > 0$.

To prove that the reward rate is decreasing in C_r, when mobile clinic is offered and d^*_s and d^*_e are corner solutions we use the $\Pi_{Pro}(\alpha^*) = 0$ properties.

$$\frac{d\alpha^*}{dC_r}\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial \alpha} + \frac{\partial \Pi_{Pro}(\alpha^*)}{\partial C_r} = 0 \implies \frac{d\alpha^*}{dC_r} \equiv -\frac{\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial C_r}}{\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial \alpha}} \tag{A.8}$$

Where $\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial C_r} = -1 + \alpha^* \frac{\partial H(d^*_s, d^*_e)}{\partial C_r}$ and $\frac{\partial H(d^*_s, d^*_e)}{\partial C_r} = \frac{3C_r - 2C_d}{\alpha^{*2} h_c}$ when $d^*_s < d^*_e$. By replacing $\frac{\partial H(d^*_s, d^*_e)}{\partial C_r}$ in $\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial C_r}$, and knowing that $d^*_e - d^*_s = 1 - \frac{3C_r - 2C_d}{\alpha^* h_c} > 0$, we can conclude that $\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial C_r} < 0$.

On the other hand, knowing that $\frac{\partial H(d^*_s, d^*_e)}{\partial \alpha^*} = -\frac{2H(d^*_s, d^*_e)}{\alpha}$, we can find the $\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial \alpha}$ as follows:

$$\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial \alpha} = \frac{h_c}{2} + H(d^*_s, d^*_e) + \alpha^* \frac{\partial H(d^*_s, d^*_e)}{\partial \alpha^*} = \frac{h_c}{2} - H(d^*_s, d^*_e) \tag{A.9}$$

From section 3.2, we know that $\frac{h_c}{2} - H(d^*_s, d^*_e) > 0$. Therefore, $\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial \alpha} > 0$. As a result $\frac{d\alpha^*}{dC_r}$ is increasing i.e. $\frac{\partial \alpha^*}{\partial C_r} > 0$.

To prove that the Medicare's total cost is increasing in C_r, when mobile clinic is offered and α^* is a corner solution, we use the property of equation A.6. Where $\frac{\partial \kappa_{Med}(\alpha^*)}{\partial \alpha} > 0$ since α^* is a corner solution and $\frac{\partial \alpha}{\partial C_r} > 0$ as concluded from equation A.9.

$$\frac{\partial \kappa_{Med}(\alpha^*)}{\partial C_r} = (1 - \alpha^*)\frac{\partial H(d^*_s, d^*_e)}{\partial C_r} \tag{A.10}$$

Assuming $C_r > C_d$, equation A.10 is positive, knowing that $\partial H(d_s^*, d_e^*)/\partial C_r = \frac{6C_r - 4C_d}{h_c \alpha^2}$. As all the components at the right side of equation A.6 are positive, we can conclude $\frac{d\kappa_{Med}^*}{dC_r}$ is positive when mobile clinic is offered and α^* is a corner solution.

To Prove $\frac{d\alpha^*}{dh_c}$ is decreasing when satellite is offered and α^* is an interior solution

$$\frac{d\alpha^*}{dh_c}\frac{\partial^2 \kappa_{Med}(\alpha^*)}{\partial \alpha^2} + \frac{\partial^2 \kappa_{Med}(\alpha^*)}{\partial \alpha \partial h_c} = 0 \implies \frac{d\alpha^*}{dh_c} \equiv -\frac{\frac{\partial^2 \kappa_{Med}(\alpha^*)}{\partial \alpha \partial h_c}}{\frac{\partial^2 \kappa_{Med}(\alpha^*)}{\partial \alpha^2}} \tag{A.11}$$

Where $\frac{\partial^2 \kappa_{Med}(\alpha^*)}{\partial \alpha^2} \geq 0$ and $\frac{\partial^2 \kappa_{Med}(\alpha^*)}{\partial \alpha \partial h_c} = \begin{cases} \frac{1}{\alpha^* h_c}\left(H(d_s^*, d_e^*) - \frac{h_c}{3} + \kappa_{Med}(\alpha^*)\right) & \text{if } d_s^* = d_e^* \\ \frac{1}{\alpha^* h_c}\left(H(d_s^*, d_e^*) + \kappa_{Med}(\alpha^*)\right) & \text{if } d_s^* < d_e^* \end{cases}$.

When provider offers mobile clinic, it's clear that $\frac{\partial^2 \kappa_{Med}(\alpha^*)}{\partial \alpha \partial h_c}$ is positive. We show that this result holds when the provider offers satellite. When satellite is offered, we can find the total hospitalization cost as $H(d_s^*, d_e^*) = \frac{C_d^2}{12\alpha^2 h_c} + \frac{h_c}{6} \geq \frac{h_c}{6}$. Furthermore, from equation 3.3, we know that $\kappa_{Med}(\alpha^*) \geq H(d_s^*, d_e^*) \geq \frac{h_c}{6}$. Hence, the summation of total hospitalization cost and Medicare's total cost is greater than $\frac{h_c}{3}$ and $\frac{\partial^2 \kappa_{Med}(\alpha^*)}{\partial \alpha \partial h_c}$ is positive when $d_s^* = d_e^*$. Therefore, $\frac{d\alpha^*}{dh_c}$ is negative, i.e. the reward rate is decreasing in hospitalization cost when it is an interior solution.

Similarly, we can used the provider's profit to show that the reward rate is decreasing in hospitalization cost at the corner solution:

$$\frac{d\alpha^*}{dh_c}\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial \alpha} + \frac{\partial \Pi_{Pro}(\alpha^*)}{\partial h_c} = 0 \implies \frac{d\alpha^*}{dh_c} \equiv -\frac{\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial h_c}}{\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial \alpha}} \tag{A.12}$$

Where $\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial h_c} = \begin{cases} \alpha^*(\frac{1}{6} + \frac{\partial H(d_s^*, d_e^*)}{\partial h_c}) & \text{if } d_s^* = d_e^* \\ \alpha^*(\frac{1}{2} + \frac{\partial H(d_s^*, d_e^*)}{\partial h_c}) & \text{if } d_s^* < d_e^* \end{cases}$

and $\frac{\partial H(d_s^*, d_e^*)}{\partial h_c} = \begin{cases} \alpha^*/h_c(\frac{h_c}{2} + H(\alpha^*)) & \text{if } d_s^* = d_e^* \\ -\frac{H(d_s^*, d_e^*)}{h_c} & \text{if } d_s^* < d_e^* \end{cases}$ Therefore, we can write: $\frac{\partial \Pi_{Pro}(\alpha^*)}{\partial h_c} = \begin{cases} \frac{h_c}{2} - H(\alpha^*) & \text{if } d_s^* = d_e^* \\ \frac{\alpha^*}{h_c}(\frac{h_c}{2} - H(d_s^*, d_e^*) & \text{if } d_s^* < d_e^* \end{cases}$ is positive and makes equation A.12 negative. Therefore, the reward rate is decreasing in hospitalization cost at the corner solution.

Next we prove that the optimal reward rate is a non-decreasing function of range cost (C_r) when optimal reward rate is an interior solution. From the Medicare's cost function, we know that $\frac{\partial \kappa_{Med}(\alpha^*)}{\partial \alpha} = 0$. Taking the second derivative of this function results in:

$$\frac{d\alpha^*}{dC_r}\frac{\partial^2 \kappa_{Med}(\alpha^*)}{\partial \alpha^2} + \frac{\partial^2 \kappa_{Med}(\alpha^*)}{\partial \alpha \partial C_r} = 0 \implies \frac{d\alpha^*}{dC_r} \equiv -\frac{\frac{\partial^2 \kappa_{Med}(\alpha^*)}{\partial \alpha \partial C_r}}{\frac{\partial^2 \kappa_{Med}(\alpha^*)}{\partial \alpha^2}} \tag{A.13}$$

Where $\frac{\partial^2 \kappa_{Med}(\alpha^*)}{\partial \alpha \partial C_r} = \begin{cases} 0 & \text{if } d_s^* = d_e^* \\ -\frac{2-\alpha^*}{\alpha^*}\frac{\partial H(d_s^*,d_e^*)}{\partial C_r} & \text{if } d_s^* < d_e^* \end{cases}$

We know that $\partial H(d_s^*, d_e^*)/\partial C_r = \frac{3C_r - 2C_d}{h_c \alpha^2}$ is positive. Therefore, $\frac{\partial^2 \kappa_{Med}(\alpha^*)}{\partial \alpha \partial C_r} \leq 0$. We can also replace $\frac{\partial^2 \kappa_{Med}(\alpha^*)}{\partial \alpha^2}$ in equation A.13, with $\frac{2(3-\alpha)H(d_s^*,d_e^*)}{\alpha^{*2}}$ which is a positive expression. This shows equation A.13 is either negative or zero.

To prove that Medicare's cost is decreasing in h_c, when optimal reward rate is an interior solution, we can take the same approach and get:

$$\frac{d\kappa_{Med}^*}{dh_c} \equiv \frac{\partial \kappa_{Med}(\alpha^*)}{\partial \alpha}\frac{\partial \alpha}{\partial h_c} + \frac{\partial \kappa_{Med}(\alpha^*)}{\partial h_c} \tag{A.14}$$

Since $\frac{\partial \kappa_{Med}(\alpha^*)}{\partial \alpha} = 0$, equation A.17 can be simplified as:

$$\frac{d\kappa_{Med}^*}{dh_c} = \frac{\alpha^*}{2} + (1-\alpha^*)\frac{\partial H(d_s^*, d_e^*)}{\partial h_c} \tag{A.15}$$

Where $0 < \alpha^* < 1$ and $\begin{cases} \partial H(d_s^*, d_e^*)/\partial h_c = 1/6 + \frac{\alpha}{2h_c}\partial H(d_s^*, d_e^*)/\partial \alpha & \text{if } d_s^* = d_e^* \\ \partial H(d_s^*, d_e^*)/\partial h_c = \frac{\alpha}{2h_c}\partial H(d_s^*, d_e^*)/\partial \alpha & \text{if } d_s^* < d_e^* \end{cases}$.

To find $\frac{\partial H(d_s^*,d_e^*)}{\partial \alpha}$, we use the fact that $\frac{\partial \kappa_{Med}(\alpha^*)}{\partial \alpha} = 0$.

$$\frac{d\kappa_{Med}^*}{d\alpha} \equiv \frac{h_c}{2} - H(d_s^*, d_e^*) + (1-\alpha)\frac{\partial H(d_s^*, d_e^*)}{\partial \alpha} = 0 \implies (1-\alpha)\frac{\partial H(d_s^*, d_e^*)}{\partial \alpha} = H(d_s^*, d_e^*) - \frac{h_c}{2}. \tag{A.16}$$

By replacing the terms for $\partial H(d_s^*, d_e^*)/\partial h_c$ and $\partial H(d_s^*, d_e^*)/\partial \alpha$, in equation A.17, we get:

$$\begin{cases} \frac{d\kappa_{Med}^*}{dh_c} = 1/6 + \alpha/12 + \frac{\alpha}{2h_c}(H(d_s^*, d_e^*)) & \text{if } d_s^* = d_e^* \\ \frac{d\kappa_{Med}^*}{dh_c} = \frac{\alpha}{2h_c}(h_c/2 + H(d_s^*, d_e^*)) & \text{if } d_s^* < d_e^* \end{cases} \quad \text{Therefore, } \frac{d\kappa_{Med}^*}{dh_c} > 0.$$

To prove that Medicare's cost is is increasing in hospitalization cost when satellite is offered and reward rate is a corner solution, we check the FOC.

$$\frac{d\kappa_{Med}^*}{dh_c} \equiv \frac{\partial \kappa_{Med}(\alpha^*)}{\partial \alpha}\frac{\partial \alpha^*}{\partial h_c} + \frac{\partial \kappa_{Med}(\alpha^*)}{\partial h_c} \tag{A.17}$$

where $\frac{\partial \alpha^*}{\partial h_c} = -\frac{\alpha^*}{h_c}$ and $\frac{\partial \kappa_{Med}(\alpha^*)}{\partial h_c} = \frac{\alpha^*}{h_c} * (\frac{\partial \kappa_{Med}(\alpha^*)}{\partial \alpha}) + \frac{H(\alpha^*)}{h_c}$. By substituting sub components into the equation A.17, we can determine that that $\frac{d\kappa_{Med}^*}{dh_c} = \frac{H(\alpha^*)}{h_c}$ which is positive.

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