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Analysis and Modeling of Strategic Interactions in Health Systems to Improve Patient Care Access

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by

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Dedication

To my wife, my love and partner, who fearlessly withstood the hardships of this adventure with me. This achievement is also yours. To my daughter, my treasure, who brings light and happiness into our lives.

To my parents, who taught me the importance of perseverance and always believed in me.

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Abstract

Affordable health care access that provides well-coordinated and high-quality services on time is a goal that governments and health organizations strive for. Regrettably, most countries deal with access problems that affect the population's health, such as long waiting lists for specialized medical services, overcrowding of emergency departments, and high health prices. In the present doctoral dissertation, I model and analyze the strategic interactions that inhabit the health system machinery to uncover possible structural problems that led to the aforementioned issues. The study involves operation research, data science, and game theory techniques to address the health care access predicament.

Each research topic in this document targets a single access problem; however, taken together, the findings highlight the need for better coordination and supervision in health systems. The first topic studies the waiting lists for specialized medical services considering local and regional interactions among public hospitals and governing institutions and the possible roles of private providers. The second topic focuses on the overcrowding of emergency departments considering the interactions among ambulance allocation decisions, waiting times to treatment, fairness, and efficiency. Finally, the last topic explores hospital consolidation as a factor determining high prices in health care markets where patients, insurers, and hospitals interact with each other.

Several insights to increase health care access were obtained through this dissertation. The results of the first research topic indicate that an increase in cooperation among hospitals can significantly reduce waiting lists for medical services due to the

heterogeneity of demand and resources of each institution. Furthermore, the cooperation should not be limited to local negotiations; instead, it should be expanded to regional contexts to mitigate the negative effect of selfish behaviors. The second study shows that implementing centralized decision systems for ambulance allocation can significantly reduce emergency department overcrowding. However, patient-centered models need to be considered to deliver increases in system efficiency that are fair to everyone. The last research topic indicates that increasing competition (or reducing consolidations) in health care markets reduces health prices and insurance premiums. Furthermore, expanding insurers' networks generate similar outcomes and even better results in oligopolistic scenarios. Finally, hospital consolidations do not imply an increase in quality of care, and changes in the demand (e.g., due to SARS-Cov-2) should reflect adjustments in the health policy prices.

The insights of this work can influence policy modifications to enhance health care access in developing and developed countries. Implementing the proposed frameworks will reduce mortality rates and increase the quality of life for patients.

Chapter 1: Introduction

The right to health was internationally recognized in the 1946 constitution of the World Health Organization (WHO) as a fundamental human right without distinction of socio-economical status, religion, race, or political preference [1]. One key component of the entitlements of this right is access to health care providing equal opportunity for everyone, timely treatments, and the highest attainable level of health [2]. However, nowadays, half of the world's population lacks access to essential medical services, and 100 million are forced into acute poverty due to health prices [3]. The lack of access to health care affects developing and developed countries [4, 5, 6]. In 2019 in the United States (US), 66.5% of all bankruptcies were tied to medical issues, and more than 26 million people did not have health insurance at any moment during the year [7, 8]. The Office of Disease Prevention and Health Promotion in the US identify four barriers to health care access: lack of availability, high cost of care, inadequate coverage, and lack of culturally competent care [9]. A few consequences drawn from this problem are higher mortality rates and treatment costs, lower quality of life, late diagnosis, and preventable hospitalizations [9, 10, 11, 12].

To deal with the lack of access to health care, the WHO has promoted the agenda of universal health coverage (UHC), to which 193 countries subscribed through the sustainable development goals of the United Nations [13, 14]. This agenda aims to increase the number of health services available, extend them to non-covered members of the population, and reduce cost-sharing and fees. However, most countries implementing UHC are facing shortages in the health workforce [15]. At the same time, studies have shown that as the

patient cost-sharing reduces, waiting times for elective treatments increases, and the waiting lists become a device to control access to health care [16, 17]. The waiting list problem exists in developing and developed countries, such as Chile, Brazil, India, England, Canada, Italy, and Australia [18, 19, 20, 21]. Some consequences of waiting lists are emotional trauma, increased patient mortality and morbidity, and public disapproval of governments [22, 23, 24, 25, 26, 27]. In a combination of supply-side and demand-side policies, waiting time guarantees appear as a promising development to end the waiting lists [11, 27, 28, 29]. Nevertheless, the obligation of health providers to favor access over needs conflicts with the Hippocratic oath [30]. Furthermore, countries might determine the time guarantees based on selected conditions or population segments, leaving uncommon diseases or low-risk patients without timely treatment or funding [28, 31, 32, 33]. As a result, extended waiting lists for non-prioritized patients or conditions occur [22].

In the US, the health system does not align with the framework promoted by the WHO through the UHC; instead, the age and financial availability of patients determine the level of access to care and ration the demand, especially in primary care [34, 35]. In the last decades, emergency departments (EDs) have taken responsibility for public health surveillance, caring for indigent people, disaster preparedness, and primary care [36, 37]. Notwithstanding the increase in demand for and utilization of emergency services, the number of EDs, hospitals, and hospital beds in the US have decreased significantly in the last two decades [38, 39]. The disproportion between supply and demand, caused by the factors stated above, has led to the national ED overcrowding crisis [40, 41, 42]. Overcrowding has been associated with long waiting times, especially for patients who are not critically ill, thus decreasing the quality of care; increasing mortality; increasing patient walkouts; increasing

ambulance offload delays; and increasing ambulance diversion, among other externalities [43, 44, 45]. In addition to the impact perceived by patients, hospitals are facing financial losses due to walkouts and ambulance diversion as consequences of overcrowding in EDs [46].

The competition-driven health care system in the US has forced EDs to deal with unexpected demand and preventable hospitalizations [38, 47]. Moreover, health prices and health insurances, therefore health care access, have been surrendered to the market forces to find their equilibriums. Unfortunately, a constant trend in the US health system has been the increasing concentration of the health insurance industry and the increasing consolidation of health delivery organizations [48, 49]. As a consequence, the US has the highest health expenditure by gross domestic product (GDP) and per person among all countries in the Organization for Economic Cooperation and Development (OECD) [50]. However, the US has one of the lowest population coverage, only above Mexico and Costa Rica, and the worst public health coverage (among countries with public health) in the OECD [51]. This translates to a lower life expectancy and a higher avoidable mortality rate and chronic disease morbidity than the average OECD country [51]. The average health premium for family coverage in employer plans in 2020 was more than $21,000, where covered workers contributed 29% of the family coverage. This applies only to employees who benefited from employer plans, and the single coverage rose to $7,000 [52, 53].

The three significant health care access problems described above (waiting lists, ED overcrowding, and consolidation in health care markets) are a clear representation of the barriers previously discussed: lack of availability, high cost of care, inadequate coverage, and lack of culturally competent care. The objective of this dissertation is to provide methods

and strategies that aim for policy modifications to reduce extended waiting lists, decrease waiting times in EDs, and reduce health insurance premiums. In other words, to increase health care access. The proposed frameworks consider hospitals and systems characteristics, patients' needs, geographical locations, local and regional interactions, and different strategies to increase fairness in the health care system.

1.1 Intellectual Merit

This research tackles the outstanding problem of health care access and its different dimensions from the perspective of fairness and efficiency, contributing to the development of knowledge by proposing novel mathematical frameworks in the intersection of multi-objective optimization, game theory, and machine learning. The study has the potential to shed light on how competition, cooperation, and allocation affect the utilization of medical resources and characterize access levels to a health system.

1.2 Broader Impact

The doctoral dissertation results will provide insights and numerical evidence for developing public policies in the US and other countries dealing with health care access problems. Implementing the proposed frameworks and strategies will improve the experience of everyone who uses or intends to use the health systems in the US and abroad. A reduction in mortality rates and an increase in quality of life will be direct consequences of the implementation of the enhanced health systems. An adequate execution of the proposed models can provide novel ways of dealing with health care problems anchored in systems engineering methods.

1.3 Outline

The following chapters of this doctoral dissertation are organized as follows: chapter 2 studies the waiting lists problem in two-tier health care systems to enhance public and private hospital interactions. The results uncover the benefits of local and regional cooperation among governing institutions and the impact of systemic selfishness on access to health services. Chapter 3 presents novel ambulance allocation optimization frameworks for the overcrowding problem in EDs. The analysis considers disparities and fairness in the development of the strategies. The results provide evidence of the benefits of centralized decision models considering the heterogenous type of patients, demand characteristics, and geographical and facilities information. Chapter 4 explores the existing health care market among insurers, hospitals, and patients in the US. The chapter studies hospitals' horizontal consolidations and the SARS-CoV-2 pandemic impact on prices and quality. The results provide insights on how to reduce insurance premiums to increase access to health services. Chapter 5 presents the main conclusions of the critical problems analyzed in chapters 2, 3, and 4. At the end of this doctoral dissertation, the references and Appendices A, B, C, D, and E, for published, under review, and preprints are provided.

Chapter 2: Waiting Lists

Prolonged waiting lists to access health care is a primary concern for countries aiming for comprehensive and effective care due to its adverse effects on mortality, quality of life, and government approval. According to the OECD, waiting lists are worse in countries combining public insurance and low or zero patient cost-sharing [16]. Therefore, presenting a significant challenge to the UHC implementation. Chapter 2 presents two novel bargaining frameworks to reduce waiting lists for specialized medical services. Unlike previous approaches, the study integrates patient and hospital characteristics in frameworks of local and regional decisions of two-tier health care systems. The models are intended to improve public actors' synergy and integrate different roles that private providers could play to reduce waiting lists while accounting for patient prioritization. The first framework, framework A, presents local and regional negotiations among public hospitals and considers private providers a back-up system after the public network runs out of resources. Framework A is solved using the Nash bargaining solution and multi-objective optimization in a sequence of games. The second framework, framework B, implements a sequence of Nash bargaining solutions to add private hospitals as players in the local and regional negotiations of the public system. The study applies Cox proportional hazard models to estimate the priority of patients in both frameworks.

This work also analyzes the consequences of hospitals' selfishness (public and private) on the system's performance and suggests different approaches to increase service rates in selfish scenarios. The models are calibrated with 2008—2018 Chilean waiting lists

data that is publicly available under request. Appendix C displays the paper "The waiting game — how cooperation between public and private hospitals can help reduce waiting lists" that presents the research of chapter 2. This article is under third revision in the journal of *Health Care Management Science*.

2.1 Contributions of Research Topic 1

The contributions of research topic 1 are the following:

(i) This is the first work that compares two frameworks to reduce waiting lists for specialized medical services considering patients, public hospitals, private hospitals, and local and regional negotiations.

(ii) This is the first study that uses the Nash bargaining solution and multi-objective optimization to mimic the interaction among hospitals and governing institutions dealing with waiting lists and improve their synergy.

(iii) Based on real data, the study evaluates the impact of hospitals' selfishness and identifies which strategy provides the best solution to reduce waiting lists.

2.2 Main Results of Research Topic 1

The case study shows that framework A reduces the Chilean waiting lists by up to 37% using available public resources. Moreover, the bi-objective model reveals the trade-off between diagnosing unserved demand and the additional expense of using private hospitals as a back-up system. Framework B shows a reduction of up to 60% of waiting lists when private hospitals are introduced as players in the public health system. The analysis on selfishness demonstrates that local negotiations are more sensitive to this behavior than regional negotiations. In the same line with these results, public selfishness appears to have a more significant impact on the system than private selfishness. Finally, the study shows

that the prioritization of patients is an excellent mechanism to divert the negative effect of lack of cooperation toward the low-priority segments.

2.3 Future Directions of Research Topic 1

Future directions of research topic 1 include adding more health care levels (e.g., primary care) to the problem and expanding the study to new reimbursement mechanisms that could change hospitals' interactions. For example, Chile is starting a pilot program of reimbursement through diagnosis related groups (DRGs) that could increase competition and service rates among providers. Additional behavioral studies measuring the selfishness levels might prove helpful.

Chapter 3: Emergency Department Overcrowding

In the last two decades, emergency department (ED) overcrowding has become a national crisis for the US health care system. Increasing mortality rates, decreasing quality of care, financial losses due to walkouts, and ambulance diversion are some of the consequences of ED overcrowding [43, 44, 45]. Given the increasing demand for ambulance utilization [54, 55], assigning service requests to EDs becomes a vital function of emergency medical services. Chapter 3 presents new ambulance allocation models to reduce patients' total time to treatment and EDs overcrowding. Three optimization strategies are proposed, taking into account both EDs' workloads and service allocation. Unlike previous approaches, this study recognizes that minimizing total or average waiting times across all emergencies may favor certain patients over others. The first strategy, system efficiency, focuses on minimizing total times to treatment (travel times plus waiting times in EDs). The second strategy considers the reduction of disparities in addition to the system efficiency. The last strategy takes a game theory approach to generate a grand coalition between the players (patients) to improve efficiency and provide fair payoffs to emergencies.

Strategies one, two, and three are represented using mixed-integer programming and solved through single-objective optimization, multi-objective optimization, min-max technique, and the non-symmetric Nash bargaining solution. The models consider patient priorities, health conditions, quality of care, walk-ins, geographical locations, time periods, and the capability of each ED to treat the health conditions.

The study presents a numerical experiment to test the applicability and scalability of the formulation. Furthermore, the three strategies are implemented in a real data case study in Florida (US). Appendix D displays the paper "Ambulance allocation optimization model for the overcrowding problem in US emergency departments: A case study in Florida" that presents the research of chapter 3. This article was published in *Socio-Economic Planning Sciences* in 2019 [56].

3.1 Contributions of Research Topic 2

The contributions of research topic 2 are the following:

(i) This is the first work that compares three different optimization strategies to account for the conflict between efficiency and fairness in the overcrowding problem of EDs.

(ii) This study presents a centralized decision system with remote triage that considers EDs' workloads, patient priorities, different diagnoses, geographical locations, quality of care by pathology, and different time periods.

(iii) Based on numerical experiments and real data, the study identifies which strategy provides the best solution for the prolonged waiting times in EDs and incentivizes system fairness.

3.2 Main Results of Research Topic 2

Based on the case study in Florida, the analysis indicates that the utilization of either strategy results in improved time to treatment, decreased waiting times, and less EDs overcrowding. However, choosing the right strategy is vital to ensure the wellness of all patients. The first strategy provides a 31.4% reduction on the average time to treatment in the system. Nevertheless, further analysis revealed the negative effect of this first strategy

on some patients, despite the priority class assigned to them. The second strategy uses a bi-objective approach between fairness and efficiency to generate multiple combinations of solutions. This approach allows decision-makers to select a disparity and understand the trade-off between increasing efficiency and reducing the disparity. However, patients not included in the fairness objective function could increase their time to treatment to even worse levels than the current scenario. Finally, the third strategy provides a 26.4% reduction on the average time to treatment and guarantees a positive effect for every patient with respect to the current conditions.

3.3 Future Directions of Research Topic 2

Future directions of research topic 2 include the design of a hybrid strategy where a bi-objective model uses a fairness function and the non-symmetric Nash bargaining solution to generate a trade-off. This model will guarantee an improvement for every patient with respect to current conditions and allow decision-makers to focus on specific populations suffering disparities. Additional studies considering metrics to compare the strategies from an economic point of view might prove helpful.

Chapter 4: Hospital Mergers in Health Markets

In the US health care system, competition is recognized as the cornerstone to balance and reduce costs while increasing quality [57]. Nevertheless, provider and health insurance markets becoming more concentrated has been a significant trend in the last decades [58, 59, 60]. While an increase in efficiencies is expected with provider consolidation, benefiting patients and customers of health services, recent studies have found that concentrated health systems are associated with higher hospital prices, frequently observing a 20% increase or more when mergers are present in the market. Furthermore, some cases showed an association between hospital mergers and higher mortality rates, pointing that an increase in prices did not improve the quality of care [61, 62]. Chapter 4 presents a framework to mimic health market interactions among patients, insurers, and hospitals. The study compares scenarios of hospital mergers and changes in the demand (SARS-Cov-2) to understand the impact on insurance prices and quality of care. Unlike previous studies, the work provides a methodological approach to consider different levels of decision instead of a single level with different stages. Furthermore, the suggested approach is highly applicable in contrast to the methods available in the literature that are primarily restricted to theoretical analysis.

The study uses real data to build a framework including patient, hospital, and insurance characteristics. The model is calibrated based on Hillsborough County in Florida, where thousands of models are run to depict changes in the policy premiums. The framework is solved using a bi-level optimization approach combined with game theory

(Nash bargaining solution and Stackelberg game), diagonalization techniques, and the Karush–Kuhn–Tucker conditions. Appendix E displays the paper preprint "A bilevel-Nash-in-Nash model for hospital mergers in health care markets: A key to affordable care" that presents the research of chapter 4. This article will be submitted to the journal of *Health Care Management Science*.

4.1 Contributions of Research Topic 3

The contributions of research topic 3 are the following:

(i) This is the first work that integrates bilevel optimization and game theory (cooperative and competitive) approaches to solve a real scenario of US health care prices considering levels of interactions among hospitals, insurers, and patients.

(ii) This study analyses the impact of hospital oligopolies in the market equilibrium and health care access for different scenarios of agreements and demand characteristics.

(iii) Based on real data, the study provides policy recommendations to reduce the price of health care in the US and highlights the expected policy price reductions with SARS-Cov-2.

4.2 Main Results of Research Topic 3

Based on the case study in Florida, increasing hospital competition in the current market can reduce policy prices by up to 14%. At the same time, expanding insurance networks can significantly reduce policy prices in either concentrated or competitive markets, where greater benefits appear in oligopolistic scenarios. This can be an alternative to consolidation penalties to reduce health care prices. The analysis performed in the SARS-

Cov-2 scenario reveals a policy average price reduction of up to 31% due to the decrease in hospital services demand. Finally, the analysis reveals that no significant improvement in quality is found when health prices increase or when the hospital market is oligopolistic.

4.3 Future Directions of Research Topic 3

Future directions of research topic 3 include expanding the current framework to analyze insurers' consolidation and the design of a two-stage stochastic model to simulate patients demand. Additional studies performing similar analyses in other regions might prove helpful to validate this study's insights.

Chapter 5: Conclusions

Nowadays, half of the world's population lacks access to essential medical services where the 1) high cost of care, 2) inadequate coverage, 3) lack of availability, and 4) lack of culturally competent care have been recognized as the barriers to health care access. A deficient health care access carries several consequences ranging from higher mortality rates to lower quality of life. This doctoral dissertation has analyzed and modeled, to some extent, the strategic interaction in three major health care access problems: waiting lists for specialized medical services (barriers 2, 3, and 4), emergency departments overcrowding (barriers 3 and 4), and consolidation in health care markets (barriers 1, 2, and 4).

The studies presented in this dissertation have led to the following findings and conclusions. First, increasing cooperation among public providers in two-tier health care systems significantly reduces waiting lists for specialized medical services (up to 37% reduction). Having prioritization techniques embedded in the decision frameworks protects high-risk patients from the impact of lack of cooperation, and regional negotiations enhance resource utilization even in unfavorable selfish scenarios. Furthermore, despite the political circumstances, private providers can play a fundamental role in the minimization of waiting lists, either as back-up or main actors. Second, centralized decision systems using remote triage showed a significant improvement in the management of ambulance allocation compared to decentralized systems. The improvement translates into a reduction of average time to treatment (travel time plus waiting time in EDs) of up to 31%. However, further analysis revealed that conventional optimization approaches generate negative results for

certain patients to maximize the common welfare. Therefore, strategies considering fairness concepts generating patient-centered solutions (e.g., Nash bargaining solution) to reduce EDs overcrowding are needed. Third, increasing health care market competition reduces health prices and insurance premiums. Furthermore, expanding insurance networks reduces policy prices in either concentrated or competitive markets, with better results in oligopolistic scenarios. This can be an alternative to consolidation penalties to reduce health care prices. Finally, hospital consolidations do not reflect a significant increase in quality of care, and changes in the demand (e.g., due to SARS-Cov-2) should reflect adjustments in the health policy prices.

The findings highlight the importance of decision systems anchored in engineering methods to improve efficiency and fairness in health care systems. The frameworks presented in the previous sections give insights into how strategic interactions affect the utilization of medical resources and determine the health care access received by the population. This dissertation has advanced the knowledge and numerical evidence of the lack of coordination/supervision existing in health systems that policymakers could use to redesign current structures or implement incentives/penalties accordingly. Future research that expands the number of actors considered in the strategic interactions and incorporates behavioral analysis into the frameworks might prove helpful.

Health system engineering methods present enormous opportunities for improving care coordination, quality, efficiency, and fairness, which may be essential to achieve sustainable access to health care worldwide.

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Appendix A: Information about the Appendices

Appendix B presents the copyright approval of the article published in the Socio-Economic Planning Sciences Journal, which is in Appendix D. Appendix C includes a paper under review, and Appendix E shows a preprint.

Appendix B: Copyright of the Article Published in the Socio-Economic Planning Sciences Journal

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Ambulance allocation optimization model for the overcrowding problem in US emergency departments: A case study in Florida

Author: Jorge A. Acuna,José L. Zayas-Castro,Hadi Charkhgard

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BACK CLOSE WINDOW

Appendix C: The Waiting Game — How Cooperation Between Public and Private Hospitals Can Help Reduce Waiting Lists

The waiting game – how cooperation between public and private hospitals can help reduce waiting lists

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Abstract

Prolonged waiting to access health care is a primary concern for nations aiming for comprehensive effective care, due to its adverse effects on mortality, quality of life, and government approval. Here, we propose two novel bargaining frameworks to reduce waiting lists in two-tier health care systems with local and regional actors. In particular, we assess the impact of the 1) trade of patients on waiting lists between hospitals, the 2) introduction of the role of private hospitals in capturing unfulfilled demand, and the 3) hospitals' willingness to share capacity on the system performance. We calibrated our models with 2008–2018 Chilean waiting list data. If hospitals trade unattended patients, our game-theoretic models indicate a potential reduction of waiting lists of up to 37%. However, when private hospitals are introduced into the system, we found a possible reduction of waiting lists of up to 60%. Further analyses revealed a trade-off between diagnosing unserved demand and the additional expense of using private hospitals as a back-up system. In summary, our game-theoretic frameworks of waiting list management in two-tier health systems suggest that public–private cooperation can be an effective mechanism to reduce waiting lists. Further empirical and prospective evaluations are needed.

Keywords: Game theory, Operations research, Waiting lists, Universal health care, Health care delivery, Health economics

Highlights

- We study the global crisis of waiting lists for specialized medical services.
- We introduce two new quantitative frameworks to reduce waiting lists that are associated with high mortality.

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- Our formulation considers patient and hospital characteristics, local and regional negotiations, the role of private providers, resource location, and hospitals' willingness to share capacity.
- We show that our game-theoretic models can substantially improve patient care, reducing waiting lists by up to 60%.
- We provide mechanisms that can fit different countries' socio-political needs and spur cooperation among hospitals.

1 Introduction

In the last decades, waiting lists for elective medical services have been a major concern of governments and publicly funded health systems. Consequently, various studies and policy implementations have been undertaken to mitigate the problem and its effects on the population [1, 2, 3, 4]. For policymakers, waiting lists represent an issue that provokes public disapproval of government and politicians [5]. Researchers, have spent more than a century trying to find explanations to the waiting list problem and observing the negative effects on society [6].

The waiting list problem exists in developing countries, such as Chile, Brazil, and India, and in developed countries, such as England, Canada, and Australia [7, 8, 9, 1]. According to the Organization for Economic Cooperation and Development (OECD), waiting lists are even worse in countries combining public insurance and low or zero patient cost sharing [10], which are common methods to control access to care [11].

In this context, countries implementing universal health coverage (UHC) are in greater need of having a technical infrastructure to handle waiting lists compared to countries that ration their resources through the financial ability of patients to access care (e.g., the United States) [10, 12]. The main idea behind UHC is to increase access to and the quality of health services while reducing the financial burden on patients [13]. Currently, the World Bank and the World Health Organization provide technical assistance to more than 100 countries for the implementation of UHC. Furthermore, all United Nations members have confirmed the goal of having UHC by 2030 [14].

The increasing worldwide importance of universal medical services underlines the need for adequate strategies to handle waiting lists and improve the utilization of available resources. Recent studies show that waiting lists are associated with increased mortality rates, worse quality of life, and significant emotional trauma [15, 16, 17, 18, 19]. Therefore, waiting lists have become a major health concern in many OECD countries [20].

In the present work, we investigate the waiting list problem in relation to specialized medical services in a South American country–Chile– with a two-tier health system. Two mathematical frameworks are proposed to reduce waiting lists, considering system resources, patient conditions and priorities, selfishness in negotiations, and public-to-public and public-to-private hospital patient transfers. Cooperative bargaining is introduced to enhance current system interactions and take advantage of misused resources.

1.1 Background on waiting list policies

In the first decade of the new millennium, most efforts to reduce waiting lists have focused on the existence of imbalances between supply and demand. One common approach considers supply-side policies [11]. The idea behind these policies is to increase funding to expand the workforce or the physical capacity of health systems, which helps to mitigate waiting times and increase service rates. However, the evidence has shown that supply-side policies have a limited effect, where a short-term reduction in waiting times is followed by a return to previous conditions or a worsening of conditions as funding runs out [5]. Additionally, the study in [21] shows that the demand for elective procedures

is negatively correlated to waiting times and highly elastic, in some cases even more than the supply curve. Consequently, as the population expects a reduction in waiting times, the demand increases and surpasses the capacity increment of supply policies. These experiences have demonstrated that short-term efforts to increase public health expenditure may be unsuccessful in reducing waiting lists for elective medical services. This relates to the inability to address the structural elements that result in waiting lists [5].

Most recent approaches are oriented to demand-side policies or a combination of supply-side and demand-side policies. Demand policies try to define clinical thresholds below which patients do not have access to publicly funded elective medical services or to divert demand to the private system through different mechanisms. Demand-side policies are difficult to implement due to the lack of data infrastructure to define the ability of patients to benefit from medical interventions. Moreover, the need to incentivize private health insurance can represent a socio-political challenge [10, 5]. With a combination of supply-side and demand-side policies, the most promising development is waiting time guarantees [5, 20, 22, 23].

Waiting time guarantees set the maximum time a patient should wait for care. The definitions of times may vary across countries and in general will represent how much a country can invest. In some cases, waiting time guarantees are enforced by governments, but despite these efforts providers may not be able to meet the threshold of time; therefore, the guarantees become more of an aspiration than an actuality [24, 5].

A significant consequence of guaranteeing waiting times is the obligation of health professionals to favor access over need, which conflicts with the Hippocratic oath [25]. Another issue with time guarantee policies is that, in general, they do not consider the equality of suffering. For example, a country might give preference to frequent types of diseases or older groups of patients [26, 27, 28, 22], leaving patients with more uncommon diseases or low risk populations without funding or timely treatment. Consequently, even longer waiting lists for non-prioritized conditions or patients occur [15].

1.2 Literature review

Given the consequences of universal care and the widely implemented waiting time guarantees, we focus our study on models intended to improve the management of waiting lists rather than on the supply, the demand, or the combination of both. The following literature review provides interesting results and increased awareness of the efforts to reduce waiting lists for elective medical services.

The management of waiting lists can be approached based on the different understandings of the problem. Some studies have proposed focusing on the systemic issues, recognizing the impact that different actors and their relationships might have on social welfare and the importance of financial commitments. The authors in [29] built a reference framework for waiting list management in a public system. The framework included the national, regional, and hospital implications of waiting lists. Additionally, an input–output model was developed to project the demand at the regional level, making it possible to evaluate the impact of waiting lists for different scenarios. The results showed that actors at different levels of decision making can influence the availability of resources in the health system. Consequently, specific models should be designed to support communication and decision making in relation to waiting lists. In [30], a qualitative study using semi-structured interviews was conducted to identify the main factors contributing to waiting lists. The results showed that a balance between demand and supply is essential to achieve better access to medical services; however, such balance is not always feasible due to financial constraints or limited resources. The authors in [31] studied waiting lists as a mechanism to ration demand in health systems; their analysis centers around Pareto optimal wait times, public choice, and queuing theory. The results showed that suppliers, patients, and governments might not maximize social welfare. Using game theory and discrete event simulation, the study in [32] evaluated the impact of patients' choice in health systems. The conclusions highlighted the

negative impact that individual/selfish decisions have on waiting times. In [33], the authors explored the benefit of using a non-cooperative game to maximize social welfare in a kidney exchange program. The conclusions evidenced the existence of a Nash equilibrium that was also a social optimum for a two-player setting. The studies presented above have limitations that need to be mentioned. First, most of the studies do not consider the importance of prioritization algorithms. Second, they present the major systemic factors resulting in waiting lists but do not necessarily provide mechanisms to deal with the issue. Third, they do not consider the interactions of a two-tier health system where private hospitals might play a fundamental role in determining waiting lists.

An alternative research line consists of modeling programs or particular hospital settings to reduce waiting lists, highlighting the importance of detailed information about resource availability and the characteristics of waiting lists at each institution. Through multi-objective optimization, the authors in [34] attempted to improve hospital administration efficiency for surgical waiting lists. The model provided an optimal surgical schedule that maximized hospital performance and minimized unusual activities to reduce waiting lists. An analytical framework for decision support systems in relation to surgical plans was also presented. In [35], the authors studied the impact of a new referral system for non-urgent specialist appointments on waiting lists of more than two years. Two options were offered to patients—take no action if the appointment was no longer required or visit a primary physician to get a new referral using a new clinic-specific template. The results showed that the time required to get a specialist appointment was reduced from eight years to two years. Using Monte Carlo simulation, the authors in [36] explored the idea of reducing waiting lists for elective orthopedic procedures by offering earlier treatment in trauma settings that were underutilized. The results showed a possible reduction of 18% of all elective procedures, thus having a significant effect on waiting times. In [37], the authors proposed a quantum-inspired evolutionary algorithm to optimize the scheduling of elective surgical procedures. The model was tested in a simulated scenario of 2000 surgeries on a waiting list with 25 nursing beds and 10 surgery rooms. The results showed a reduction in waiting time of 16.25%. From the literature above, several contributions have emerged. However, these studies neglect the impact of system interactions, assume isolated environments, and target factors that are not necessarily the real reasons for waiting lists.

The last research line focuses on prioritizing waiting lists, which has become a significant method of improvement for different specialties. This idea includes understanding the role of justice, the severity of a patient's condition, and advanced policy models. In [38], a triage stage was implemented to reduce waiting lists for the first appointment for child mental health services. The study followed 155 patients over six months and compared the results with a control group. The method helped reduce the waiting time for the first appointment significantly, and of the original 155 patients, 82 were removed from the waiting list. In [39], the authors investigated how patients are prioritized under policies of time guarantees. Through empirical analysis of patient-level data, they built a Poisson regression model to relate the number of days patients spend on waiting lists to observed patient characteristics. Their results showed that doctors in general prioritized patients according to the severity of their condition, even when no formal policy for prioritization is in place. In [40], a rule-based prioritization criterion was implemented to improve the management of waiting lists, considering waiting time and justice. The study demonstrated that timeliness considerations are insufficient to manage waiting lists properly and that justice should be included in the prioritization models. Based on the studies above, prioritization techniques have become a key component in improving the management of waiting lists. Nevertheless, prioritization models do not reduce waiting lists unless patients are removed from the queue before treatment. The last limitation shows the importance of prioritization models as a complement to techniques aiming to reduce waiting lists.

The reviewed literature focused on three major aspects: the systemic issues or structural elements of waiting lists, models to reduce waiting lists in individual programs or hospital settings, and prioritization techniques to manage waiting lists. Several findings emerged from these efforts: the negative role

that isolate decisions play in social welfare, the need to include fairness in mathematical models, and the importance of provider communication in the health system.

1.3 Contributions

As shown by [29], actors at different levels of decision making can influence the performance of a health system. In this paper, our objective is to reduce waiting lists for specialized medical services by improving current system interactions. Unlike previous approaches, we integrate patient and hospital characteristics in a framework of local and regional decisions of a two-tier health system. Our models are intended to improve public actors' synergy and integrate the different roles that private providers could play to reduce waiting lists while accounting for patient prioritization. Additionally, we show the consequences of hospitals' selfishness on the system's efficiency. The resulting mathematical models enable health planners and government entities to assess the potential benefits of policy implementation. We illustrate these approaches with a setting in Chile. However, our methodologies and frameworks can be contextually applied to countries with similar structures.

1.4 The Chilean health system

Chile has a two-tier health care system, with a public expenditure of 4.5% of the gross domestic product (GDP). In 2017, for the first time the public health expenditure matched the private health expenditure [41]. Despite this, the imbalance between the demand received by public and private hospitals is still a source of significant inequality [42]. Approximately 78% of the population is covered by the public network, and the remaining population is covered by private or military insurance [43, 44]. The public system is divided strategically into six macro-regions to manage the health system. Each macro-region has two or more Regional Health Services (RHSs), with a total of 29 RHSs that administer and supervise the provision of health care at all levels [45].
In 2005, the government of Chile implemented a policy that included waiting time guarantees, known as garantías explícitas en salud (GES, health explicit guarantees), to limit waiting time and the financial burden on patients, while increasing access to and quality of care for a select group of conditions [46, 47, 48, 15]. The prioritized health conditions were chosen based mainly on social preference and the level of burden of disease [22]. Today in Chile, 85 conditions are covered by GES [49]. These consume the most public health resources, thus causing lengthy waiting lists for non-prioritized or non-GES conditions [50]. In 2018, the Chilean Ministry of Health registered 1,801,937 patients who did not receive care for non-prioritized elective medical appointments. In the first half of 2018 (January–June) alone, 9,364 patients died while waiting for treatment [51]. In other words, 18.5% of the total deaths in Chile were patients waiting for care, and only 3.4% of the deaths were associated with external causes of mortality [51, 52].

1.4.1 Operational aspects

In 2017, the Chilean government defined a set of administrative policies for the national system of RHSs. The idea was to regulate the utilization of public resources considering efficiency and efficacy. The two main additions to the system were the creation of the macro-regional purchasing directories and the incorporation of budget guidelines for the acquisition of health services. Purchasing directories have two main goals–to optimize the purchase of private and public providers' services and to provide technical recommendations vis-à-vis the needs of RHSs. According to the national report [42], during 2017 the purchasing directories produced better coordination among RHSs in terms of resolving waiting lists for specialized medical services, both GES and non-GES. Guideline nine officialized the acquisition of services provided by private providers; however, the idea behind this protocol is to keep track of purchases, and it is not restrictive in nature [42]. Therefore, the purchasing directories

evaluate and help coordinate the interaction among public and private providers, including hospitals, while guideline nine makes the financial interaction official.
In parallel to the improvements described above, the government is implementing new information technology, the Sistema de Gestión de Tiempos de Espera (SIGTE, Waiting Times Management System). This platform was designed to keep track of patients on waiting lists and to detect bottlenecks in the network. At the same time, SIGTE provides a solid base for the utilization of electronic medical records throughout the country and should enable the use of prioritization algorithms to reduce mortality associated with waiting lists [51].
From a financial perspective, the two major funds that coexist in the Chilean health system are the Fondo Nacional de Salud (FONASA, National Public Health Fund) and the Instituciones de Salud Previsional (ISAPRES, Private Health Insurers). However, there is no coordination between these two systems [53]. The fund assignment process of the public system aims to keep the cost of health services low and to promote high service rates. However, the assignment of funds considers compromises of production (expected number of patients to be served) that are not related to the actual demand but rather to statistics from the previous year. Furthermore, the production that surpasses the annual agreement is not reimbursed. In contrast, a budget that is not entirely utilized implies a reduction in funds for the next year, promoting expenditure over efficiency [54]. In 2020, the first high-complexity hospitals with diagnosis related groups (DRG) systems started transitioning to a new payment mechanism. The idea behind this new approach is to fund hospitals with a fixed amount of the global budget (with limits) and a variable amount based on the number of patients served classified by DRG. This new funding mechanism is expected to increase the hospitals' efficiency and split the financial risk between FONASA and the providers [55].
Based on the information in this section, expert opinions, and a report [56], a graphical representation of system interactions was built. Figure 1 shows two macro-regions with different sets of RHS supervising medical centers providing primary, secondary, and tertiary levels of care. The black arrows represent administrative interactions, while the red arrows represent the movement of patients inside the system. Depending on the existence of agreements with FONASA, private hospitals might be under the monitoring of RHSs or might be supervised directly by the health superintendence. Even if rare, transfers of patients among macro-regions happens when technologies or procedures are not available at specific locations. Similarly, patients on waiting lists might go to private providers in certain circumstances, such as lack of technology in the public system or agreements between FONASA and private providers.

1.5 Structure

The rest of the article proceeds as follows. Section 2 introduces the main definitions and methods used in this study. Section 3 describes the mathematical formulation for each framework and the notations needed. Section 4 presents the Chilean case study. Section 5 presents the results of implementing our models in the case study. Finally, Section 6 discusses the main findings and presents the conclusions of this study.

2 Methods

Based on the problem description, a combination of consecutive games, machine learning, and multi-objective optimization is implemented to mimic and enhance the health system in Chile, providing alternatives for reducing waiting lists for specialized medical services. We then present some ideas and definitions to facilitate understanding of the methodologies.

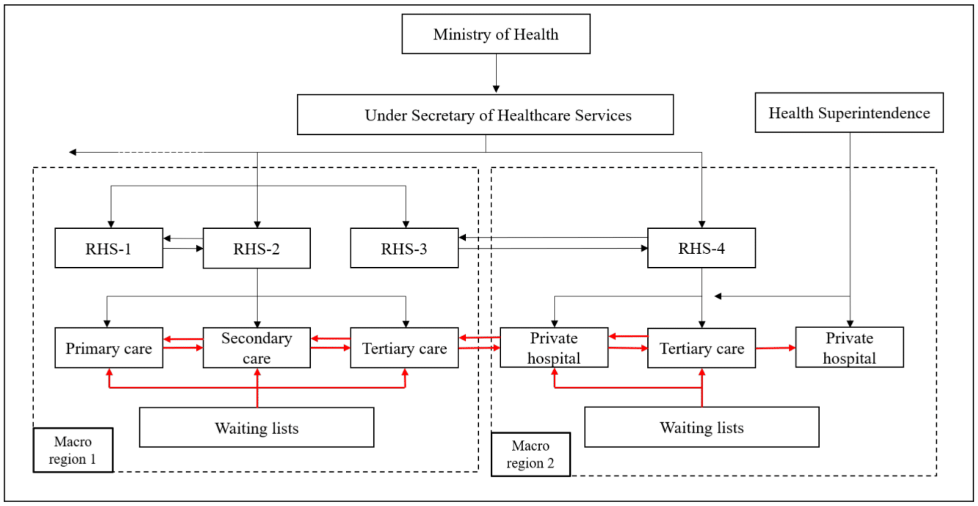

Figure 1: Chilean health system interactions. Abbreviations: RHS = Regional Health Service

2.1 Preliminaries

2.1.1 Multi-objective optimization

Consider the general formulation of a multi-objective optimization model:

$$\max_{z \in \mathcal{Z}} f_1(z), f_2(z), ..., f_p(z),$$

where $\mathcal{Z}$ represents the feasible set in the decision space, and $f_k(z)$ is the linear objective function of entity k, from $k = 1, ..., p$. Let us define the image of $\mathcal{Z}$ in the objective/criterion space as $\mathcal{W} = f(\mathcal{Z})$.

Definition: A feasible solution $z' \in \mathcal{Z}$ is called efficient or Pareto optimal if there is no other $z \in \mathcal{Z}$ such that $f_k(z) \geq f_k(z')$ for $k = 1, ..., p$ and $f(z) \neq f(z')$. If z' is efficient, then $f(z')$ is called a *nondominated point*. The set of all efficient solutions $z' \in \mathcal{Z}$ is denoted by $\mathcal{Z}_E$. The set of all nondominated points $f(z') \in \mathcal{W}$ for some $z' \in \mathcal{Z}_E$ is denoted by $\mathcal{W}_N$ and referred to as the *nondominated frontier* or the *efficient frontier* [57].

2.1.2 Nash bargaining solution

The Nash bargaining solution (NBS) is a cooperative approach to address the bargaining problem in which players need to share a payoff or cost that they jointly generate. In this case, the players create a grand coalition instead of competing with each other to get better payoffs or lower costs. The NBS yields a unique and Pareto optimal solution. Let u_k for $k = 1, ..., p$ be the utility function of player k and d_k be the disagreement point or status quo (payoff without cooperation) of player k. The NBS is the point $z \in \mathcal{Z}$ obtained from the following optimization problem.

$$\max_{z \in \mathcal{Z}} \prod_{k=1}^{p} (u_k(z) - d_k)$$

Two important axioms relating to bargaining games are individual rationality and Pareto optimality. The first one establishes that no player will accept a payoff lower than the disagreement point. The second introduces the trade-off among the players when a solution has been obtained. Thus, the solution guarantees that the payoff for one player cannot be increased without negatively affecting the payoffs of other players [58, 59, 60].
As mentioned, we use a sequential approach to model the waiting list for specialized medical services. This implies a set of consecutive games and optimization problems with different hierarchies to represent how decisions are made and influence themselves. For example, local agreements can impact regional trades or the relationship with private providers, thus impacting the feasible set of the regional model. We developed two frameworks with different mathematical phases to represent system interactions among public hospitals, RHSs, and private hospitals.

3 Mathematical formulation

We designed two frameworks to model the system, framework A and framework B. The first framework (A) has three phases of decisions—local, regional, and private. The local phase occurs when public hospitals of the same RHS bargain their waiting lists. The regional phase is solved after finding the solution to the local negotiations. It considers the RHS utilities as a function of the hospitals under their supervision; in this case, the bargaining of waiting lists occurs through the different RHSs. In the private phase, private hospitals are involved in helping to clear the remaining waiting lists, after phases one and two as a back-up to the system. In the second framework (B), private hospitals are part of the local and regional negotiations instead of being a back-up system. This implies that private hospitals are considered as players in the two bargaining phases but have a different type of utility function compared to public hospitals.
Let M be the exogenous set of patients on waiting lists that could be transferred to another institution to get service. N denotes the set of hospitals in the system that may need to transfer patients and/or are willing to receive patients. Let H represent the set of RHSs under analysis. The set of private hospitals is defined by L. Finally, let P represent the set of specialized medical services required by patients. Each patient $z \in M$ is modeled by a triplet (p, w_z, i), where p represents the specialized medical service needed, w_z represents the priority code assigned to patient z, and i is the hospital where patient z is on the waiting list for a specialized medical service. Every hospital $i \in N$ is also modeled by a triplet (h, c_{ip}, δ_i), where h represents the RHS that supervises i, c_{ip} is the remaining capacity of hospital i (after assignment to its internal demand) to treat patients with a need for specialty p, and δ_i is the selfishness level of hospital i. In the literature, selfishness has been used to describe hospital managers' behaviors or greed [61, 62], to define certain health care routing decisions [63], and to describe noncooperative network agents [64]. In our formulation, the exogenous parameter of public selfishness represents the lack of desire to share capacity with other providers due to, for example, compromises of production, the difference in payments based on patients' origin, or concern about future demand. Table 1 summarizes all indices, parameters, and variables required for the mathematical formulations.

Next, we introduce the frameworks' formulation and describe the modification required in each phase.

3.1 General constraints

The formulation of our two frameworks is based on mixed-integer programming (MIP). To begin we introduce the general constraints. Let x_{ijp}^{z} denote a binary variable that represents patient z with a need for specialized medical service p. If the value is equal to one, it indicates that patient z has been transferred from i to j to get specialized medical service; otherwise, it is zero. Constraint (1) represents

Table 1: Indices, parameters, and decision variables of the formulation.

Index	Definition
i	Hospital i, where $i \in N$
j	Hospital j, where $j \in N$ and $j \neq i$
z	Patient z, where $z \in M$
p	Specialty p, where $p \in P$
l	Private hospital l, where $l \in L$
h	Health service h, where $h \in H$
Parameter	**Definition**
w_z	The priority code assigned to patient z
c_{ip}	Remaining capacity of hospital i to treat patients with specialty p
δ_i	Selfishness factor of hospital i
δ_l	Selfishness factor of private hospital l
θ_{ih}	Utility of hospital i that belongs to health service h before negotiations (disagreement point)
k_{ih}	Binary parameter equal to 1 if hospital i belongs to health service h
s_{ij}	Binary parameter equal to 1 if hospitals i and j belong to the same health service
d_{il}	Binary parameter equal to 1 if hospitals i and l belong to the same health service
a_{pl}	Available capacity per specialty p at private hospital l
b_{lh}	Binary parameter equal to 1 if private hospital i belongs to health service h
ω	Maximum value of priority among all patients
Ψ_p	Difference in the price paid between public and private network for specialty p
ϵ	A small value to avoid mathematical errors (e.g., 10^{-6})
Variable	**Definition**
x^z_{ijp}	1 if patient z with a need for specialized medical service p that belongs to hospital i is transfered to hospital j, 0 otherwise
x^z_{ilp}	1 if patient z with a need for specialized medical service p that belongs to hospital i is transfered to private hospital l, 0 otherwise
t_i	Utility of hospital i based on the number of patients transfered to other institutions
y_i	Utility of hospital i based on the remaining capacity
u_{ih}	Total utility of hospital i that belongs to health service h
u_{lh}	Total utility of private hospital l that belongs to health service h
σ_l	Total number of patients received by private hospital l
u_l	Total utility of private hospital l
r_i	Total utility of hospital i

the fact that a patient can be transferred at most to one new hospital location.

$$\sum_{i \in N} \sum_{\substack{j \in N \\ j \neq i}} \sum_{p \in P} x^z_{ijp} \leq 1 \quad \forall z \in M \tag{1}$$

Given that each hospital has a limited capacity per medical specialty, constraint (2) ensures that the number of patients being transferred to a given institution does not surpass its capacity.

$$\sum_{\substack{j \in N \\ j \neq i}} \sum_{z \in M} x^z_{jip} \leq c_{ip} \quad \forall p \in P \quad \forall i \in N \tag{2}$$

Two major elements determine the utility function of each public hospital. The first element is the number of patients on the hospital's waiting lists that is being transferred to other institutions to receive service. The second element is related to the remaining capacity after the negotiations. In (3), the utility of each public hospital transferring patients to other institutions is presented. The function considers the priority of each patient w_z to calculate the total value of each transfer.

$$t_i = \sum_{\substack{j \in N \\ j \neq i}} \sum_{z \in M} \sum_{p \in P} w_z x^z_{ijp} \quad \forall i \in N \tag{3}$$

Constraint (4) shows the second element of the utility function. As mentioned, the number of patients received by each hospital through the negotiations reduces the available capacity per specialty for future demand. Therefore, this element decreases the utility as more patients are accepted. The magnitude of the effect over the utility is determined by the level of each institution's selfishness δ_i. At the same time, future demand with different priorities could use the slots available for a specialty. Therefore, we considered a unique value common to all patients and institutions, ω. The parameter ω helps obtain a more robust solution by considering the scenario where the patients in worse condition (highest priority) use the available slots. Consequently, each institution's selfishness δ_i and the highest priority ω represent the loss of potential gain when sharing an availability instead of keeping it for themselves.

$$y_i = \omega \sum_{p \in P} (c_{ip} - \sum_{\substack{j \in N \\ j \neq i}} \sum_{z \in M} x^z_{jip}) \delta_i \quad \forall i \in N \tag{4}$$

As a result, constraint (5) combines the elements of constraints (3) and (4) into the total utility function of public hospitals. Binary parameter k_{ih} is equal to 1 if hospital i belongs to RHS h and is 0 otherwise.

$$u_{ih} = k_{ih}(t_i + y_i) \quad \forall i \in N \quad \forall h \in H \tag{5}$$

In (6), a simpler representation of the utility function of each hospital is introduced.

$$r_i = \sum_{h \in H} u_{ih} \quad \forall i \in N \tag{6}$$

Based on patients' information, constraint (7) fixes the value of some variables as equal to zero.

$$x^z_{ijp} = 0 \quad \forall z \in M \quad \forall i \notin N_z \quad \forall p \notin P_z \quad \forall j = i \in N \tag{7}$$

Constraints (8)–(12) define the range and type of variables used in the models.

$$x^z_{ijp} \in \{0, 1\} \quad \forall i \in N \quad \forall j \neq i \in N \quad \forall p \in P \quad \forall z \in M \tag{8}$$

$$t_i \in \mathbb{R}^+ \quad \forall i \in N \tag{9}$$

$$y_i \in \mathbb{R}^+ \quad \forall i \in N \tag{10}$$

$$u_{ih} \in \mathbb{R}^+ \quad \forall i \in N \quad \forall h \in H \tag{11}$$

$$r_i \in \mathbb{R}^+ \quad \forall i \in N \tag{12}$$

3.2 Framework A

3.2.1 Phase one (local public negotiations)

Phase one consists of the local public hospitals' negotiations. As mentioned, the NBS can be used to find a unique Pareto optimal solution to cooperative bargaining, in this case among public hospitals. The maximization of hospitals' utilities through cooperative bargaining is represented by objective function (13). Constraint (14) establishes the axiom of individual rationality; no hospital will accept a payoff (utility) lower than the disagreement point. The status quo or disagreement point θ_{ih} is calculated based on the utility function (5) of each hospital before negotiations. It becomes evident that the element of (5) represented by constraint (3) is going to always be zero before bargaining. At the same time, the element represented by constraint (4) can be equal to zero if the selfishness δ_i is zero. Otherwise, it will take the value of the total available capacity multiplied by the maximum priority, ω, and δ_i. Given that phase one is restricted to local negotiations, constraint (15) guarantees that no trade takes place outside the RHS.

$$\max \prod_{i \in N} (r_i - \sum_{h \in H} \theta_{ih}) \tag{13}$$

subject to (1)–(12) and

$$r_i \geq \sum_{h \in H} \theta_{ih} \quad \forall i \in N \tag{14}$$

$$x^z_{ijp} \leq s_{ij} \quad \forall i \in N \quad \forall j \neq i \in N \quad \forall p \in P \quad \forall z \in M \tag{15}$$

3.2.2 Phase two (regional public negotiations)

Phase two describes the regional public hospitals' negotiations in which RHSs' payoffs are considered. Each RHS's utility is calculated considering the hospitals under its supervision as the difference between the sum of all public hospital utilities minus the sum of all disagreement points. In this way, each RHS's utility becomes a function of individual utilities, where the RHS protects the interest of the institutions under its supervision. The objective function (16) represents the cooperative bargaining among RHSs, while constraint (14) guarantees that no hospital receives a utility lower than its disagreement point. In the regional phase, the solution obtained in the local bargaining helps to define the feasible space of phase two. In other words, the matrix of variables x^z_{ijp}, the set M, the disagreement points of each public hospital θ_{ih} (depending on capacity), and the remaining capacity per specialty of each hospital c_{ip} are updated. Constraint (17) ensures that all hospitals' transfers take place outside their RHS.

$$\max \prod_{h \in H} \sum_{i \in N} (u_{ih} - \theta_{ih}) \tag{16}$$

subject to (1)–(12), (14) and

$$x^z_{ijp} \leq 1 - s_{ij} \quad \forall i \in N \quad \forall j \neq i \in N \quad \forall p \in P \quad \forall z \in M \tag{17}$$

3.2.3 Phase three (private hospitals as a back-up)

Phase three considers the decisions after local and regional negotiations have used all available public resources. The idea behind this level of analysis is to measure the financial impact of using private hospitals as a back-up system to help clear the remaining waiting lists. Therefore, as well as in the regional phase, the matrix of variables x^z_{ijp} and the set M are updated based on the previous phase solution. Phase three requires the incorporation of the binary variables x^z_{ilp}; similar to x^z_{ijp}, x^z_{ilp} is equal to one if patient z with a need for specialized medical service p from public hospital i is transferred to private hospital l and is equal to zero otherwise. This multi-objective model of two functions (bi-objective) generates a nondominated frontier representing the trade-off between minimizing the number of patients on waiting lists, objective function (19), and minimizing the additional cost of serving patients in the private system, objective function (18). The formulation does not include a selfishness term because the back-up role is financially driven and does not conflict with the private providers' profit maximization goal.
Similar to constraint (3), (20) calculates the utility of transferring patients to private hospitals acknowledging their priority. In (21), the additional cost of utilizing the private system is calculated. Ψ_p represents the difference between the price paid in the private network and the price paid in the public system for the same specialized medical service p. Through constraint (22), we consider the fact that patients are transferred to private hospitals.

$$\min \sum_{l \in L} u_l \tag{18}$$

$$\min \sum_{z \in M} w_z - \sum_{i \in N} t_i \tag{19}$$

subject to (1), (9), and

$$t_i = \sum_{l \in L} \sum_{z \in M} \sum_{p \in P} w_z x^z_{ilp} \quad \forall i \in N \tag{20}$$

$$u_l = \sum_{i \in N} \sum_{z \in M} \sum_{p \in P} x^z_{ilp} \Psi_p \quad \forall l \in L \tag{21}$$

$$x^z_{ilp} \in \{0, 1\} \quad \forall i \in N \quad \forall l \in L \quad \forall p \in P \quad \forall z \in M \tag{22}$$

Next, we present framework B, which is independent of the three phases already described. Framework B considers phases in which private hospitals are not a back-up for the public system. Instead, they become active participants in the local and regional negotiations.

3.3 Framework B

3.3.1 Phase one (local negotiations)

Phase one of framework B presents the first local negotiations in which private hospitals become part of the bargaining. This model uses the NBS to solve the cooperative bargaining problem and considers a new utility function for private hospitals. As can be observed in the objective function (23), most of the equation is equivalent to the model presented in phase one of framework A, except for the new term of private utilities u_{lh}. Constraint (24) captures the total number of patients being received by each private hospital with their respective priorities w_z. This variable, σ_l, is used by constraint (25) to generate a concave utility function for each private institution. The private selfishness term δ_l combined with the available capacity per specialized service a_{pl} determines the maximum value attainable for the concave function. This implies the existence of a point after which private hospitals

lose utility for receiving patients from the public system. Defining a concave utility function for private hospitals is consistent with realities in which private insurers pay more for service to providers than public insurers. In (25), ϵ represents a small number to avoid numerical issues when δ_l is equal to one. In our case, we chose an ϵ of 10^{-6} to avoid changes in the value of u_{lh} when δ_l is different than one. Constraint (26) guarantees that no hospital negotiates outside its RHS.

$$\max \left(\prod_{i\in N}(r_i - \sum_{h\in H}\theta_{ih})\right)\left(\prod_{l\in L}\sum_{h\in H}u_{lh}\right) \tag{23}$$

subject to (1)–(12), (14), (15), (22), and

$$\sigma_l = \sum_{i\in N}\sum_{z\in M}\sum_{p\in P}x^z_{ilp} \quad \forall l\in L \tag{24}$$

$$u_{lh} = b_{lh}\left(-\frac{1}{(1+\epsilon-\delta_l)a_{pl}}(\sigma_l)^2 + 2(\sigma_l)\right) \quad \forall l\in L \quad \forall h\in H \tag{25}$$

$$x^z_{ilp} \le d_{il} \quad \forall i\in N \quad \forall l\in L \quad \forall p\in P \quad \forall z\in M \tag{26}$$

3.3.2 Phase two (regional negotiations)

Phase two of framework B describes the negotiations among public and private providers that take place at the regional level. Like in phase one, the private hospitals are included in the objective function (27) but in this case are also part of the RHS's objective function. This implies that the social benefit generated by private hospitals is accounted for in the utility function of the RHS. In the regional phase, the solution obtained from the local bargaining helps to define the feasible space of phase two. This means that the matrix of variables x^z_{ijp} and x^z_{ilp}, the set M, the remaining capacity per specialty of each hospital c_{ip} and a_{pl}, and the disagreement points of each public hospital θ_{ih} are updated. Constraint (28) guarantees that patients can only be transferred to private hospitals outside their RHS.

$$\max \prod_{h\in H}\left(\sum_{i\in N}(u_{ih}-\theta_{ih}) + \sum_{l\in L}u_{lh}\right) \tag{27}$$

subject to (1)–(12), (14), (17), (22), (24), (25), and

$$x^z_{ilp} \le 1 - d_{il} \quad \forall i\in N \quad \forall l\in L \quad \forall p\in P \quad \forall z\in M \tag{28}$$

3.4 Transformation of the models

As the NBS presented in phases one and two of both frameworks (A and B) has a non-linear objective function, two possible approaches can be used to solve it. We can either use a non-linear solver or transform it into a second-order cone problem (SOCP). In general, the latter option has the advantage of being efficiently solved by commercial solvers, such as CPLEX, GUROBI, and XPRESS. As an example, let us consider phase one of framework A with the following general form.

$$\max \prod_{i\in N}(r_i - \sum_{h\in H}\theta_{ih})$$

subject to (1)–(12) and

$$r_i \ge \sum_{h\in H}\theta_{ih} \quad \forall i\in N$$

$$x^z_{ijp} \le s_{ij} \quad \forall i\in N \quad \forall j\ne i\in N \quad \forall p\in P \quad \forall z\in M$$

It was shown in [59] that mathematical problems with the structure presented above can be formulated as a mixed-integer SOCP. To begin, a new non-negative variable γ and a geometric constraint are added to the model. To avoid computational issues with the geometric constraint, a set of non-negative variables and constraints replace it. Let κ be the smallest integer value such that $2^{\kappa} \geq np$, where np represents the number of players in the game. After adding the set of non-negative variables γ and τ, phase one of framework A can be reformulated as:

$$\max \gamma$$

subject to (1)–(12),(14),(15), and

$$0 \leq \gamma \leq \Gamma$$
$$0 \leq \Gamma \leq \sqrt{\tau_1^{\kappa-1}\tau_2^{\kappa-1}}$$
$$0 \leq \tau_j^l \leq \sqrt{\tau_{2j-1}^{l-1}\tau_{2j}^{l-1}} \quad \forall j = 1,..,2^{\kappa-l} \quad \forall l = 1,..,\kappa-1$$
$$0 \leq \tau_j^0 = r_j - \sum_{h\in H}\theta_{jh} \quad \forall j = 1,..,np$$
$$0 \leq \tau_j^0 = \Gamma \quad \forall j = np+1,..,2^{\kappa}.$$

Another issue encountered with nonlinear functions relates to private hospitals. In phases one and two of framework B, the utility function is defined as a concave function of patients being received and their priorities. A common practice to deal with concave or convex functions is to use a piecewise linear function to represent it. The advantage of implementing a piecewise linear function is that advanced mixed-integer linear programming techniques can be applied. However, using an approximation in the original function requires checking that the estimate is close enough to the original point [65, 66]. An example of a piecewise linear approach for a concave function is depicted in Figure 2. To generate line segments that approximate the function in constraint (25), we use the following general equation.

$$L_{x_0} = f(x_0) + f^{'}(x_0)(x - x_0)$$

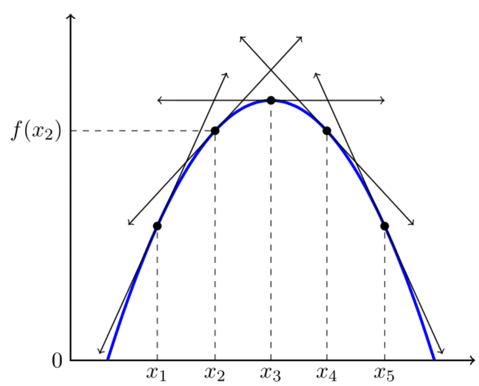

Figure 2: Example of a piecewise linear concave function built using five linear equations

In (25), $f(x_0)$ is represented by u_{lh} evaluated in the point x_0, while $f^{'}(x_0)$ is the derivative of $f(x_0)$ with respect to σ_l evaluated in x_0. Consequently, the concave private hospitals' utilities become a set of lines where every value of σ_l can generate a segment.

4 Case study

This section presents a case study based on the Chilean scenario. Data was collected from de-identified and publicly available (by request) waiting list databases from separate RHSs—Atacama, Valparaiso-San Antonio, and Osorno [67]. These three RHSs typify the natural divisions of the country, being located in the north, center, and south of Chile, respectively. The dataset includes information about patients on waiting lists for non-prioritized specialized medical services from 2008 to 2018 at 77 public medical centers providing primary, secondary, and tertiary levels of care. A total of 35 specialties are included, and four levels of priorities (low, moderate, considerate, and high) were estimated. The priority code is an outcomes-driven estimation of the mortality risk of a patient on a waiting list using the algorithm presented in [15]. Essentially, we estimate the ratio of the hazard rates corresponding to the 35 specialized services in our waiting list cohort. These hazard ratios were adjusted for age, sex, residence, insurance coverage, and level of care. Similar outcome-driven waiting list prioritization schemes are currently used by Chile's Ministry of Health [68]. For more details about the results of hazard ratios, consult Table 3 in Appendix A.

Given that the data for the years 2008 and 2018 were not completely collected, they were not involved in our analysis of demand. Based on the hospitals' historical utilization levels, the available capacity of each public institution was calculated. The demand in 2017 was chosen to be analyzed using our models because it is the most recent. Outliers were removed from the dataset using the interquartile range rule [69].

In an initial exploration, we found that of the 137,516 patients on waiting lists in 2017 among the three RHSs, 23,107 never received medical services or a proper diagnosis. Therefore, we use our models to target the unfulfilled demand of 2017, which has the highest mortality rate in recent years [51]. Figure 3 shows the geographical location of each RHS and their 2017 unmet demand. Based on meetings the authors held with experts from the Chilean Ministry of Health and their valuable feedback and onsite experience, public hospitals' selfishness was defined as the degree of concern about sharing capacity with other hospitals based on the directors' evaluation system, funding mechanisms, or compromises of production, that might jeopardize their ability to meet future demand. In essence, this is a system-induced behavior that inhibits proper collaboration. In the case of private hospitals, which are driven by their financial results, selfishness represents the amount of capacity they are willing to share with the public system, given the risk of sacrificing higher payments from patients with private insurance.

The private hospitals' available capacity for phases one and two of framework B was estimated based on the 46% historical participation in the provision of specialized medical services in Chile [70]. For phase three of framework A, the additional cost of serving patients in private hospitals was calculated from the difference in the appointment price per medical specialty between the public system [71] and a private hospital in Santiago (capital of Chile) [72]. The second column in Table 2 presents the additional cost per specialty of diagnosing one patient in the private network.

5 Results

This section provides the results of the case study evaluated in our two frameworks. The MIP phases were implemented in JULIA 1.1.0 and solved using CPLEX 12.9.0. Given the database's size and the complex computational operations, we executed the models considering a monthly demand and capacity. The values were calculated as the average demand and capacity per specialty and medical center. This approach can also be considered as a change in the scale factor of the demand and capacity. Consequently, solving a single month of waiting lists is proportional to solving a full year of demand. Table 2 shows the details of demand and capacity per specialty, where a deficient assignment of resources is observed. For example, maxillofacial surgery has an unfulfilled waiting list of 182 patients per month and zero available resources to bargain among the RHSs. However, traumatology

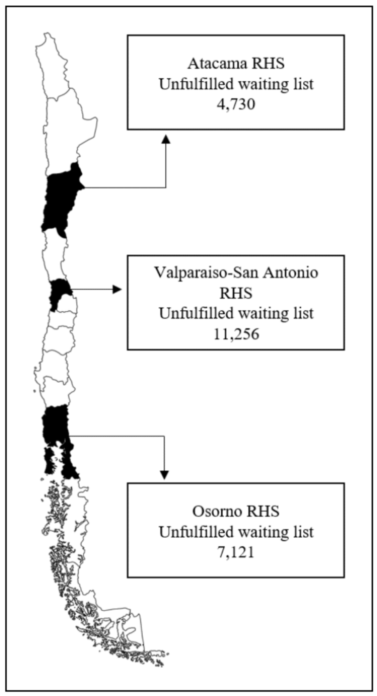

Figure 3: Unfulfilled waiting lists per the selected RHSs. Abbreviations: RHS = Regional Health Service

has an unfulfilled monthly waiting list of 39 patients but 162 units of capacity available among the RHSs. Despite having a few specialties with zero demand or capacity (making transfers impossible), we included them in our study to generalize the frameworks to the Chilean health system. Moreover, in scenarios with additional RHSs, the unfulfilled demand or underutilized capacity could match new medical centers' needs and resources.
In Figure 4, the total demand per specialty and their average priority are presented. As can be observed, the two most extensive waiting lists are for ophthalmology and dentistry with a low average priority, which seems reasonable considering that people with low-priority medical needs should wait longer when resources are scarce. However, immediately after these two specialties, the average priority level goes up, implying higher mortality rates.

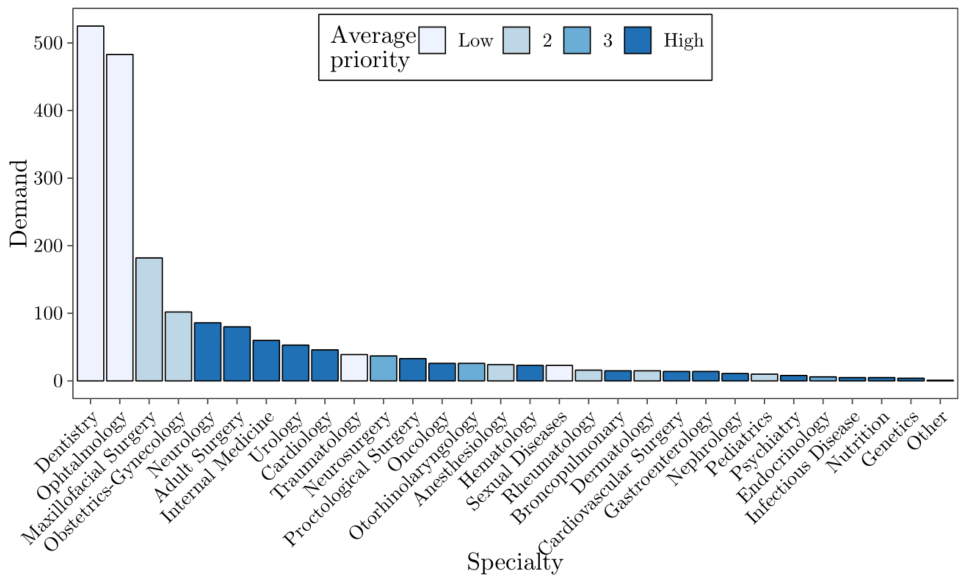

Figure 4: Total monthly demand per specialty with average priority

5.1 Framework A

Next, we present the results obtained in the different phases of framework A considering the percentage of demand fulfilled, the transfers per specialty, the impact of public hospitals' selfishness, and private hospitals' role as a back-up system.

5.1.1 Transfers in phases one and two

Table 2 shows the results per RHS of the local and regional public negotiations (phases one and two, respectively) considering the selfishness factor, δ_i, being equal to zero. The last two rows of the table present the total number of patients who received service and the percentage of demand that those transfers fulfilled. As can be observed at the local level, the Atacama and Valparaiso-San Antonio RHSs show a reduction of waiting lists. In contrast, Osorno RHS shows zero transfers upon the local negotiations. This might imply better coordination at the local level in the Osorno RHS, enabling the

full utilization of needed resources. In Table 2, we also present the results of regional public negotiations (phase two of the series of games) that take place after the local bargaining considering the remaining demand and capacity (updated feasible space). In this case, all RHSs show a reduction of waiting lists. The most significant improvement occurs in the Osorno RHS with 31.3% of demand being satisfied, equivalent to 190 patients receiving medical service. In contrasting phases one and two, we observe that the Atacama RHS benefits more from the local negotiations with 211 vs. 17 transfers. In the case of the Valparaiso-San Antonio RHS, the benefits obtained from local and regional bargaining are similar with 174 and 127 transfers, respectively. We already saw that local negotiations have a greater impact on reducing waiting lists than regional bargaining for the Atacama RHS. However, the number of transfers per medical specialty show that the few regional transfers are for cardiology and infectious diseases, two high-priority (mortality) specialties. In contrast, the largest number of transfers at the local level is in ophthalmology, a low-priority specialty. In the Valparaiso-San Antonio RHS case, the number of patients getting service per specialty at the local and regional level is similar. Nevertheless, local bargaining serves patients with higher priorities, such as neurology, gynecology, and internal medicine. In the regional negotiations, the most significant transfer occurs in ophthalmology, which is the specialty with the smallest number of patients served in the local phase. Osorno RHS only shows regional transfers with a combination of priority levels, such as gynecology (medium-high), traumatology (low), and urology (high). In Table 2, the last column aggregates the number of patients served per specialty due to phases one and two of framework A, considering δ_i is equal to zero.

5.1.2 Public selfishness

The main goal of our study is to reduce waiting lists by improving providers' synergy through enhancing interaction structures. Accordingly, the impact of different scenarios of selfishness needs to be examined. Given that the results presented so far have focused on the best possible scenario for public negotiations, selfishness factor δ_i equal to zero, Figure 5 depicts a sensitivity analysis of δ_i with values ranging between 0 and 1. This sensitivity analysis shows the impact that public selfishness can have on the number of patients receiving service at the local and regional levels. The first outcome that can be observed in Figure 5 is the quick decrease in transfers with local negotiations and the small increase in regional transfers when the value of δ_i starts to increase. This can be explained considering the limited alternatives to negotiate at the local level. As selfishness starts to grow in the system, certain providers could run out of options locally to negotiate, for example, an RHS where only two hospitals provide service for a given specialty. This implies that fewer resources are used in the local negotiations that can be bargained at the regional level, where by default there is a higher number of negotiating providers. The growth of selfishness among public hospitals is related to the capacity being offered, which translates into a deterioration in performance that can jeopardize the reduction of waiting lists to the point of complete stagnation (selfishness equal to one) of negotiations. The second outcome of the sensitivity analysis of our framework refers to the importance of having a good prioritization system combined with allocation strategies. Figure 6 shows the impact that selfishness has on the number of patients receiving service per priority. As can be observed, the priority curves decay in the same order as their importance. Despite having the highest demand and one of the largest numbers of patients being served, low-priority specialties are first in decay after selfishness starts to increase. In contrast, medical services of high and considerable priority last longer in the system, guaranteeing proper utilization of resources for all scenarios.

5.1.3 Private hospitals as a back-up system

In Table 2 column two shows the additional cost (beyond the public expense) per medical specialty of providing an appointment for a single patient at a private hospital. The bi-objective model, phase three, generates a nondominated frontier of solutions between the unfulfilled demand and the additional

Table 2: Framework A input data and results for phases I and II with zero selfishness.

Specialty	Additional cost†	Demand‡	Capacity‡	Atcama		Valparaiso*		Osorno		Total I & II
				PH I	PH II	PH I	PH II	PH I	PH II	
Adult SX	18	80	14	0	0	1	13	0	0	14
Anesthesiology	18	24	1	0	0	1	0	0	0	1
Breast SX	18	0	23	0	0	0	0	0	0	0
Bronchopulmonary	0	15	19	0	0	9	0	0	6	15
Cardiology	0	46	26	0	12	14	0	0	0	26
Cardiovascular SX	0	14	6	0	0	1	0	0	5	6
Dentistry	18	525	0	0	0	0	0	0	0	0
Dermatology	16	15	77	0	0	0	0	0	15	15
Endocrinology	0	6	8	0	0	2	0	0	4	6
Family Medicine	29	0	3	0	0	0	0	0	0	0
Gastroenterology	0	14	25	3	0	10	1	0	0	14
Genetics	0	4	24	0	0	0	4	0	0	4
Hematology	0	23	2	0	0	2	0	0	0	2
Infectious Disease	0	5	6	0	5	0	0	0	0	5
Internal Medicine	0	60	110	16	0	39	5	0	0	60
Maxillofacial SX	0	182	0	0	0	0	0	0	0	0
Nephrology	10	11	18	0	0	3	0	0	8	11
Neurology	0	86	51	12	0	23	0	0	16	51
Neurosurgery	0	37	22	0	0	13	4	0	5	22
Nutrition	19	5	4	0	0	4	0	0	0	4
Gynecology	18	102	231	9	0	28	0	0	65	102
Oncology	0	26	4	0	0	0	4	0	0	4
Ophtalmology	0	483	215	164	0	1	50	0	0	215
Other	18	1	8	0	0	0	0	0	1	1
ENT	16	26	284	6	0	15	5	0	0	26
Pediatrics	4	10	27	1	0	0	0	0	9	10
Physical Medicine	10	0	41	0	0	0	0	0	0	0
Plastic SX	18	0	5	0	0	0	0	0	0	0
Proctological SX	10	33	0	0	0	0	0	0	0	0
Psychiatry	7	8	57	0	0	8	0	0	0	8
Rheumatology	24	16	0	0	0	0	0	0	0	0
Sexual Diseases	24	23	5	0	0	0	5	0	0	5
Traumatology	24	39	169	0	0	0	0	0	39	39
Urology	10	53	111	0	0	0	36	0	17	53
Total		1972	1596	211	17	174	127	0	190	719
% of Demand		100	80.93	52.36	8.9	18.1	16.1	0	31.3	36.46

Abbreviations: PH, phase; SX, surgery; ENT, ear, nose, and throat; PH I, local transfers; PH II, regional transfers

† Additional cost of diagnosis in the private network in US dollars

‡ Average monthly values

* Valparaiso-San Antonio regional health service

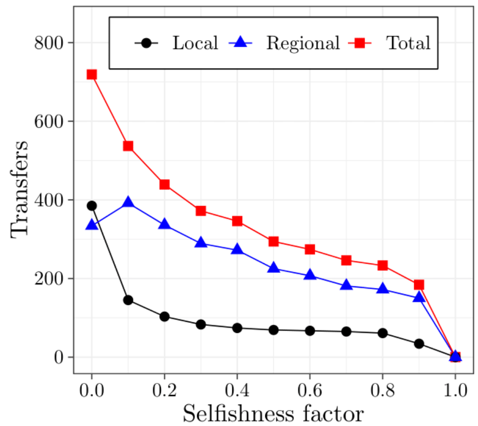

Figure 5: Impact of selfishness on public interactions

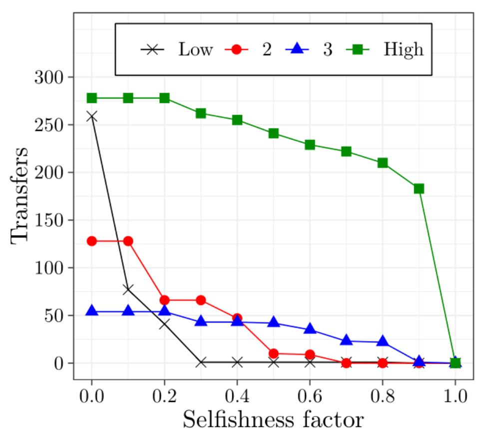

Figure 6: Impact of selfishness per priority level in public interactions

expense needed to diagnose the unserved patients in the private network. In Figure 7, the trade-off between unfulfilled demand (y-axis) and additional expense (x-axis) is shown. As explained in the preliminaries, the improvement of one objective function can only be obtained by the deterioration of the other objective function. Therefore, every point in the nondominated frontier is an optimal solution that the decision maker can choose based on the available resources or desired fulfillment of demand. Figure 7 highlights the point (5809,350) at which the value in the x-axis is the median of the additional expense curve; however, any point in the curve can be considered for analysis and selected by the decision maker.

Figures 8 and 9 present the number of transfers to the private network per specialty when the chosen

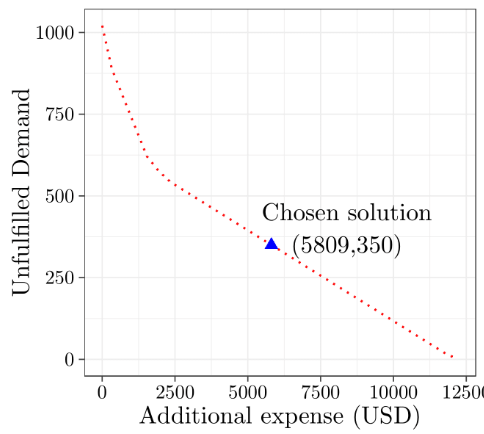

Figure 7: Nondominated frontier, trade-off between unfulfilled demand and additional expense

solution is the above-mentioned point (5809,350). In Figure 8, the color of the columns is determined by the additional cost of the medical specialties. It can be seen that most of the columns have light colors, indicating a system preference for specialties with a low additional cost. In contrast, the color of the columns in Figure 9 changes based on the average priority of each specialty. In this case, most of the columns are darker than in Figure 8, indicating a preference for specialties with high priority. Despite the inclination for high-priority specialties, the first two columns of Figure 9 are low priority. This can be explained, considering that most of the high-priority patients have already been served in phases one and two.

5.2 Framework B

Next, we present the results obtained from the local and regional phases of framework B. Figure 10 and Figure 11 show a sensitivity analysis of the public and private selfishness conducted for phases one and two, respectively. In these formulations, the private hospitals are not a back-up system. Rather, they become players that actively participate in the local and regional negotiations. To deal with the private providers' concave utility function, we used a piecewise function that consists of five linear pieces that produced an objective value variation of 10^{-3} with respect to four linear pieces, which is negligible considering the range of objective values obtained. Figure 12 summarizes the impact of selfishness on the system and presents the total number of transfers in framework B.

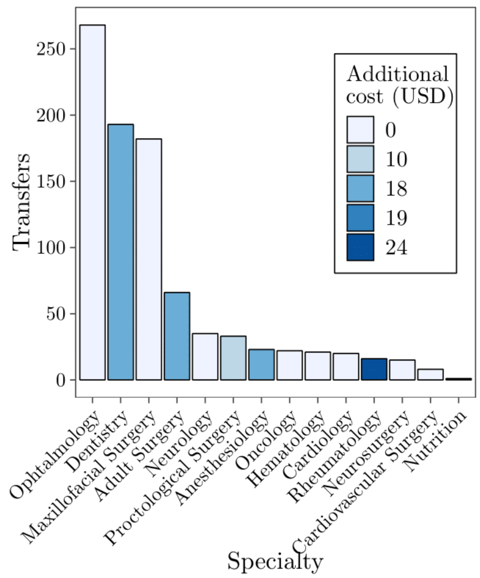

Figure 8: Number of transfers to private network per specialty and additional cost

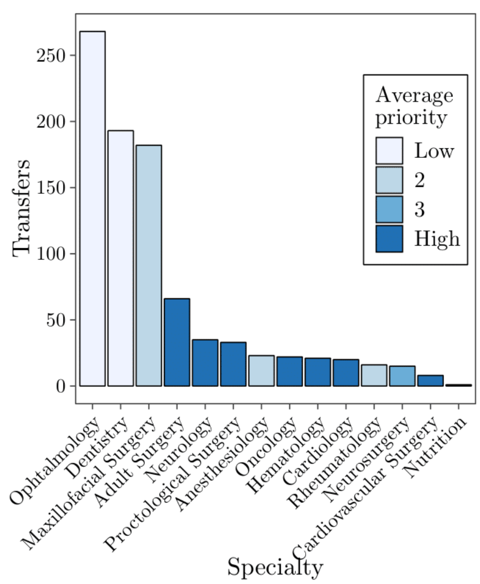

Figure 9: Number of transfers to private network per specialty and priority

5.2.1 Selfishness in local and regional negotiations

In addition to the public network, framework B considers a private setting of three artificial hospitals, one per RHS, with a total of 600 units of combined capacity, approximately 46% of system participation. We ran 121 models of local and regional negotiations to build the surfaces presented in Figures 10 and 11. In Figure 10, the local negotiations are subject to the changes in the factors δ_i (public selfishness) and δ_l (private selfishness) between 0 and 1. From the generated surface, we observe that public and private selfishness negatively affect the number of patients receiving medical service. However, the reduction related to private selfishness is steadier. This ties to the fact that private hospitals have a different utility function that only considers the patients being received; consequently, the δ_l factor is the single element defining their willingness to negotiate. In the case of public hospitals, a combination of δ_i and the number of patients sent to other hospitals defines the willingness to share. Therefore, as a public provider becomes more selfish, a double negative effect is generated. First, the hospital shares less capacity, thus affecting other institutions. Second, given that other institutions have to reduce their transfer of patients to the selfish hospital, each balance between patients in and out (utility functions) is affected, reducing the capacity sharing of these institutions.

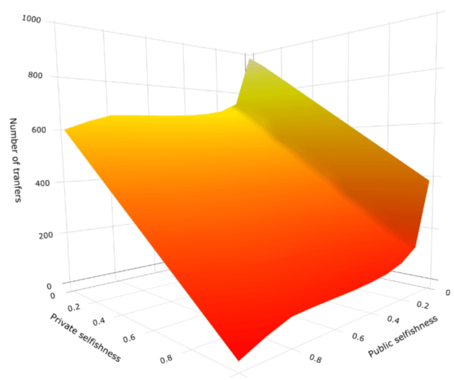

Figure 10: Effect of private and public selfishness on local bargaining

Figure 11 shows the sensitivity analysis for phase two of framework B. When public selfishness increases, the number of transfers is reduced. Conversely, when private selfishness increases, a larger number of patients receive service. Given that the results of the regional phase build upon the results of the local phase, the dependency of Figure 11 on Figure 10 becomes evident. In local negotiations, if private selfishness increases, the public hospitals are forced to look for resources in the regional bargaining. Conversely, adding private resources to the local network is a good way to avoid regional bargaining in circumstances of high public selfishness.

5.2.2 Transfers in framework B and the selfishness effect

Figure 12 shows the total impact of the selfishness factors in the reduction of waiting lists. The increase in the values of δ_i or δ_l reduces the number of transfers. Furthermore, it can be seen that public selfishness has a greater impact on the service rate, which can be explained by a combination of factors. First, a larger number of players are affected by public selfishness. Second, the increase in private selfishness generates a small improvement in the regional service rate that smoothes its overall negative effect. Finally, public hospitals receive almost double the number of transfers than private

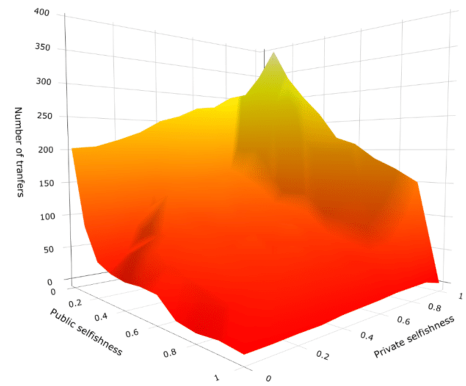

Figure 11: Effect of private and public selfishness on regional bargaining

hospitals in the best scenario, affecting a more substantial part of the population. In total, framework B was capable of serving 1179 patients when both parameters of selfishness were equal to zero.

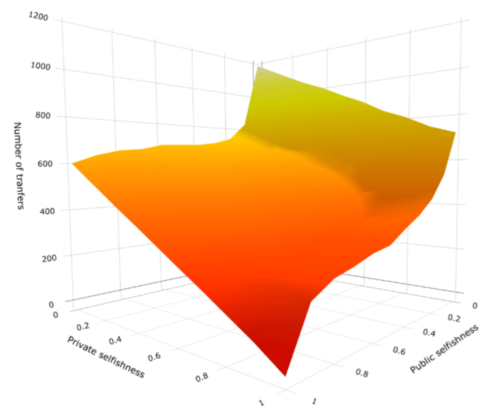

Figure 12: Effect of private and public selfishness on the total number of transfers

6 Discussion and conclusions

Increased mortality rates, low quality of life, and public disapproval of governments are some of the consequences of waiting lists for specialized medical services. We propose two frameworks to study system-level mechanisms to reduce waiting lists through consecutive cooperative games and multi-objective optimization. Our models enhance public hospitals' and Regional Health Services' (RHSs) interactions and consider the role that private hospitals might have in the reduction of waiting lists. Additionally, we analyze the impact of selfishness among public and private providers on the health network.

Our case study is based on the Chilean health system where phases one and two of framework A reduced waiting lists, which are not prioritized by the government, by up to 37% using the available public resources. We also found that each RHS benefits from bargaining in different ways. Osorno benefits only from regional negotiations (phase two) with mixed priorities. This result aligns with recent rankings positioning Osorno RHS in first place for the management and integration of medical centers in its network [73, 74]. Valparaiso-San Antonio reduces waiting lists with both levels of negotiations (phases one and two). However, it is the only RHS benefiting from the trade of patients requiring sexual diseases specialists. This situation might relate to having the largest harbor in the region. Studies have shown that harbors require special attention vis-à-vis sexually transmitted diseases [75, 76]. Atacama benefits from local and regional negotiations but is the only RHS that does not transfer patients to bronchopulmonary specialists. An intuitive explanation relates to the RHS being located in the desert. Studies have shown that meteorological parameters are correlated to respiratory problems [77, 78]. Taken together, these findings highlight the importance of tailored waiting lists designed to satisfy the heterogeneous needs of each region that could be determined by factors such as demographic characteristics, the availability of specialists and equipment, weather conditions, financial resources, and health system management [79, 80, 81].

We performed a sensitivity analysis of public selfishness for our framework A, phases one and two. The results show that local negotiations are more sensitive to selfishness and that regional bargaining helps to maintain a higher service rate, even in unfavorable selfish scenarios. However, a prioritization index that ensures patients who are at most risk are at the front of the queue plays a fundamental role in reducing the effect of the system's selfishness. In our models, the prioritization action diverted the negative impact of lack of cooperation toward the low-priority segments.

To reduce the waiting lists even further, we propose two possible roles for private hospitals. In the first (framework A, phase three), private providers act as a back-up system after the public network runs out of medical resources. We found that this approach could generate a set of alternative trade-offs between the additional expense of serving patients in private hospitals and the reduction of waiting lists. According to our cost assumptions, to ensure that each patient in the remaining monthly demand (at selfishness zero) gets to be seen by a physician in the private system, an additional $US12,000 (beyond what it would cost in the public system) is needed. This translates into a total annual cost of serving remaining patients from the three RHSs in the private network of approximately $US700,000 (interested readers can find the total private appointment cost per specialty in [72]).

In framework B, private hospitals became players in the local and regional negotiations. Consequently, private and public selfishness could jeopardize the reduction of waiting lists. We found that public selfishness has the worst impact on the system due to the number of players (public hospitals) and the amount of demand (patients) it affects. However, an increase in private selfishness forces public hospitals to look for resources outside their regions, implying higher costs and discomfort for patients. Similar to framework A, regional negotiations are an excellent way to mitigate the negative effect of public selfishness. However, framework B showed that regional negotiations introduce a more significant improvement in private selfishness because public providers can still help each other. By combining public resources and private hospitals' participation as players, framework B reduced the unfulfilled waiting list by up to 60% when selfishness was equal to zero.

To deal with the selfishness in the health care systems, economic incentives for those helping other institutions or penalties for those not willing to cooperate might prove helpful. Another approach consisting of waiting list credits (total capacity shared) that can be regained in times of need from other institutions can be attractive for providers. A similar approach is utilized in the energy markets where credits can be sold among regions [82].

From a policymaker's point of view, contrasting our theoretical results (selfishness equal to zero) and the results after implementing these frameworks provides a good mechanism to obtain approximated parameters of selfishness. There a few points to highlight regarding the applicability of each frame-

work. First, both frameworks can improve public resource utilization, but private hospitals' role will define which approach suits a country's needs better. For example, framework A considers the private providers a back-up system; consequently, it does not require sizable political alignment concerning private providers' participation in the public health system. However, framework A implies a higher expenditure on public health. Framework B requires private providers' involvement as active members in delivering public health care. This can create political and social discomfort in countries with a preference for public health providers, particularly if there is selfishness on the part of private providers. In addition, it requires private providers' willingness to deal with the externalities of providing public goods, and the experience of various countries has shown mixed results regarding private actors participating in the delivery of public care [83].

From a managerial perspective, the number of transfers in our models is equivalent to the system capacity utilization in each framework. Therefore, the sensitivity analysis performed between selfishness and the number of transfers can also be interpreted as the relationship between selfishness and the system capacity utilization (see Appendix B for more details).

Another interesting analysis is comparing our frameworks with a fully centralized assignment model adopting a maximization of the weighted sum of the utility functions. As in our model and given the problem's characteristics (lack of resources in some specialties and excess in others), the centralized model's solution would also allocate all the required/available resources (check Table 2 to see our model's allocation with zero selfishness). However, this method diverges from our solution because the distribution of resources will not align with demand in terms of geographic location. Additionally, it has been shown that centralized models using a weighted sum of functions do not necessarily produce a fair distribution of benefits, and the estimation of weights can be subjective. Conversely, the NBS ensures that the benefits are distributed fairly among the players (hospitals/RHSs) [84]. Interested readers may refer to [60, 85] to see the Nash approach's effectiveness in other problems.

Based on the insights derived from our models and data, we believe the Chilean government and its SIGTE have an excellent opportunity to facilitate the local and regional trade of waiting lists among public and private hospitals. For example, to manage the SARS-CoV-2 pandemic, the Chilean government has established a set of instructions to coordinate the public and private networks through the supervision of the Under Secretary of Health Services (see Figure 1) [86]. However, the design of the SARS-CoV-2 coordinated system could be evaluated or improved with a model such as the one presented in this study. In addition, the Chilean government's efforts to introduce the DRG funding mechanism can also help deal with selfishness due to budgets based on production compromises. As mentioned, private hospitals' support of the public system is subject to each country's internal politics. Opening the public demand equally for private and public hospitals represents a challenge not only from the financial and ethical viewpoints but also from the perspective of quality of care. Given the current inequalities between the public and private health systems in Chile [87], private hospitals' back-up role might increase access to a higher quality of care for those in the greatest need without generating a disruptive demand migration.

Our work has some modeling assumptions and data limitations. First, the frameworks require an information system that can frequently provide the status of waiting lists per specialty throughout the country. They also require patient prioritization models that can support the decisions. From the data perspective, our study estimated the priorities using non-clinical patient information, and the additional cost values for private providers were based on the prices of a single private hospital. Additionally, our models do not consider information related to patients' mobility and do not penalize the distance traveled in the regional transfers. In practice, relaxing the last assumptions will imply a reduction in the percentage of improvement. Finally, we assume an absence of uncertainty in relation to the waiting lists; a model considering possible increases in demand due to the improvement in waiting times might be helpful for policymakers. Despite these limitations, our approaches establish strong evidence of how to reduce waiting lists by increasing cooperation. Furthermore, generalizing

these frameworks to other countries with and without two-tier health care systems is possible as long as the modeling assumptions are satisfied and the limitations considered.
To our knowledge, this is the first work that combines MIP optimization models with game theory to reduce waiting lists for people requiring specialized medical services. The mathematical frameworks presented in this study provide a quantitative tool for the design of a centralized system to enhance interactions among public and private providers. Policymakers can use the proposed models to determine incentive structures that will promote bargaining for the benefit of patients. Future research that relaxes some of the assumptions and limitations of this work or behavioral studies measuring the selfishness levels might prove helpful.

Declarations

Competing interests: The authors declare no competing interests.

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Availability of data and material: The waiting lists datasets are publicly available and can be requested from the Chilean government through:
https://portaltransparencia.cl/PortalPdT/.

The interpretations and reporting of these datasets are the responsibility of the authors and in no way should be seen as an official policy of or interpretation by the medical centers, Regional Health Services, the Ministry of Health of Chile, or the Government of Chile.

Appendix A

Table 3: Hazard ratio for mortality within two years of listing according to patient characteristics.

	Overall‡ N=987,497		Atacama† N=264,756		Valparaiso-San Antonio† N=457,928		Osorno† N=264,813	
	N (%)	HR (95% CI)	N (%)	HR (95% CI)	N (%)	HR (95% CI)	N (%)	HR (95% CI)
2-Year Mortality Rate	33,546 (3.40)		7,334 (2.77)		18,408 (4.02)		7,804 (2.95)	
Age (15-45 C)								
0-3	68,028 (7)	0.76 (0.69-0.84)***	18,405 (7)	0.77 (0.6-0.99)*	34,224 (7)	0.78 (0.69-0.87)***	15,399 (6)	0.31 (0.21-0.45)***
4-7	53,865 (5)	0.16 (0.12-0.2)***	14,893 (6)	0.21 (0.13-0.34)***	24,158 (5)	0.15 (0.11-0.21)***	14,814 (6)	0.09 (0.04-0.19)***
8-11	43,053 (4)	0.1 (0.07-0.14)***	12,793 (5)	0.08 (0.04-0.19)***	19,580 (4)	0.11 (0.07-0.16)***	10,680 (4)	0.05 (0.02-0.16)***
12-14	35,723 (4)	0.18 (0.14-0.24)***	10,178 (4)	0.22 (0.12-0.39)***	16,895 (4)	0.16 (0.11-0.23)***	8,650 (3)	0.17 (0.09-0.35)***
15-45	293,892 (30)		84,265 (32)		125,589 (27)		84,038 (32)	
46-55	146,814 (15)	2.88 (2.72-3.05)***	39,404 (15)	2.94 (2.59-3.34)***	66,267 (14)	2.79 (2.58-3.01)***	41,143 (16)	2.93 (2.6-3.31)***
56-65	139,099 (14)	5.47 (5.19-5.76)***	35,391 (13)	6.49 (5.8-7.27)***	67,223 (15)	4.88 (4.55-5.24)***	36,485 (14)	5.77 (5.17-6.43)***
66-75	122,319 (12)	9.11 (8.66-9.57)***	29,264 (11)	12.22 (10.96-13.61)***	61,731 (13)	7.58 (7.08-8.1)***	31,324 (12)	10.15 (9.14-11.26)***
76-85	70,835 (7)	16.11 (15.32-16.94)***	17,130 (6)	20.14 (18.06-22.46)***	35,495 (8)	13.63 (12.74-14.59)***	18,210 (7)	18.13 (16.34-20.12)***
85+	13,869 (1)	31.77 (30.01-33.63)***	3,033 (1)	43.11 (38.1-48.79)***	6,766 (1)	27.18 (25.15-29.37)***	4,070 (2)	32.16 (28.63-36.12)***
Sex (Female C)								
Female	613,499 (62)		166,045 (63)		282,601 (62)		164,853 (62)	
Male	373,998 (38)	1.65 (1.61-1.69)***	98,711 (37)	1.75 (1.67-1.84)***	175,327 (38)	1.66 (1.61-1.71)***	99,960 (38)	1.51 (1.44-1.58)***
Residence (Other C)								
Rural	20,271 (2)		16,267 (6)		1,854 (1)		2,150 (1)	
Other	320,563 (32)	1.72 (1.56-1.89)***	36,555 (14)	1.98 (1.77-2.23)***	36,258 (8)	1.5 (1.21-1.84)***	247,750 (94)	1.44 (0.91-2.26)
Urban	646,663 (65)	1.19 (1.09-1.31)***	211,934 (80)	1.13 (1.02-1.26)*	419,816 (92)	1.2 (0.98-1.47)	14,913 (6)	0.85 (0.52-1.39)
Health Service (Atacama C)								
Atacama	264,756 (27)							
Osorno	457,928 (46)	Std Dev=0.02		Not applicable		Not Applicable		Not Applicable
Valparaiso-San Antonio	264,813 (27)							
Health Insurance (Public C)								
Public	979,666 (99)		263,420 (99)		453,985 (99)		262,261 (99)	
Other (Private, Military)	7,831 (1)	0.85 (0.73-0.99)*	1,336 (1)	0.75 (0.5-1.12)	3,943 (1)	0.73 (0.58-0.92)**	2,552 (1)	1.15 (0.91-1.47)
Specialty (Internal Med C)								
Internal Medicine	46,767 (5)		19,054 (7)		20,829 (5)		6,884 (3)	
Adult Surgery	71,148 (7)	0.67 (0.64-0.7)***	16,667 (6)	0.91 (0.83-1)*	37,534 (8)	0.55 (0.52-0.58)***	16,947 (6)	0.74 (0.66-0.82)***
Anesthesiology	3,978 (1)	0.38 (0.33-0.44)***	0 (1)	Not applicable	3,365 (1)	0.34 (0.29-0.39)***	613 (1)	0.28 (0.17-0.47)***
Breast Surgery	1,478 (1)	0.55 (0.39-0.77)***	0 (1)	Not applicable	1,478 (1)	0.52 (0.37-0.73)***	0 (1)	Not applicable
Pulmonary	17,427 (2)	1.17 (1.1-1.24)***	3,028 (1)	2.05 (1.8-2.32)***	9,222 (2)	1.02 (0.94-1.1)	5,177 (2)	0.96 (0.84-1.09)
Cardiology	31,480 (3)	0.66 (0.63-0.7)***	6,473 (2)	0.87 (0.77-0.98)*	16,583 (4)	0.6 (0.56-0.64)***	8,424 (3)	0.59 (0.53-0.67)***
Cardiovascular Surgery	15,197 (2)	0.63 (0.58-0.68)***	2,453 (1)	1.05 (0.88-1.24)	5,687 (1)	0.56 (0.51-0.62)***	7,057 (3)	0.51 (0.44-0.58)***
Dentistry	128,505 (13)	0.33 (0.31-0.36)***	17,538 (7)	0.5 (0.43-0.57)***	74,765 (16)	0.37 (0.32-0.42)***	36,202 (14)	0.22 (0.19-0.25)***

Table 3 Hazard ratio for mortality within two years of listing according to patient characteristics (continued).

	Overall‡ N=987,497		Atacama† N=264,756		Valparaiso-San Antonio† N=457,928		Osorno† N=264,813	
	N (%)	HR (95% CI)	N (%)	HR (95% CI)	N (%)	HR (95% CI)	N (%)	HR (95% CI)
Dermatology	28,987 (3)	0.42 (0.38-0.46)***	11,076 (4)	0.62 (0.54-0.72)***	6,261 (1)	0.39 (0.34-0.46)***	11,650 (4)	0.3 (0.25-0.36)***
Endocrinology	17,854 (2)	0.43 (0.39-0.49)***	3,836 (1)	0.48 (0.36-0.65)***	9,662 (2)	0.42 (0.36-0.48)***	4,356 (2)	0.36 (0.28-0.47)***
Gastroenterology	25,745 (3)	1.03 (0.98-1.09)	5,057 (2)	1.3 (1.14-1.48)***	13,282 (3)	0.93 (0.86-1)*	7,406 (3)	0.97 (0.86-1.1)
Genetics	3,348 (1)	0.64 (0.46-0.89)**	2,267 (1)	0.54 (0.33-0.89)*	1,081 (1)	1.06 (0.69-1.64)	0 (1)	-
Hematology	5,868 (1)	1.6 (1.49-1.73)***	0 (1)	Not applicable	2,929 (1)	1.14 (1.02-1.27)*	2,939 (1)	1.89 (1.68-2.13)***
Infectious Disease	3,304 (1)	0.86 (0.7-1.05)	628 (1)	0.61 (0.34-1.1)	2,676 (1)	0.8 (0.65-0.99)*	0 (1)	Not applicable
Maxillofacial Surgery	18,140 (2)	0.37 (0.31-0.43)***	3,472 (1)	0.37 (0.25-0.55)***	4,494 (1)	0.3 (0.22-0.41)***	10,174 (4)	0.39 (0.31-0.48)***
Neonatology	282 (1)	1.61 (0.84-3.12)	0 (1)	Not applicable	282 (1)	1.32 (0.68-2.56)	42 (1)	0.00 (0-9.99)
Nephrology	11,208 (1)	1.02 (0.96-1.1)	1,975 (1)	1.01 (0.85-1.2)	6,659 (1)	1 (0.91-1.08)	2,574 (1)	0.89 (0.76-1.04)
Neurology	47,087 (5)	0.82 (0.78-0.86)***	12,899 (5)	1.13 (1.01-1.26)*	23,795 (5)	0.72 (0.66-0.77)***	10,393 (4)	0.75 (0.67-0.85)***
Neurosurgery	15,238 (2)	0.5 (0.46-0.55)***	2,856 (1)	0.96 (0.78-1.18)	7,667 (2)	0.43 (0.38-0.48)***	4,715 (2)	0.43 (0.35-0.51)***
Nutrition	1,856 (1)	2.16 (1.81-2.57)***	0 (1)	Not applicable	1,702 (1)	1.82 (1.52-2.17)***	154 (1)	0 (0-4.334E+252)
Obstetrics Gynecology	93,979 (10)	0.42 (0.39-0.45)***	24,228 (9)	0.47 (0.4-0.56)***	48,395 (11)	0.41 (0.38-0.45)***	21,356 (8)	0.35 (0.29-0.42)***
Oncology	6,080 (1)	3.57 (3.4-3.76)***	1,080 (1)	3.71 (3.24-4.26)***	3,285 (1)	2.64 (2.47-2.83)***	1,715 (1)	5.19 (4.68-5.75)***
Ophthalmology	113,848 (12)	0.34 (0.32-0.36)***	43,852 (17)	0.5 (0.46-0.55)***	30,438 (7)	0.32 (0.29-0.34)***	39,558 (15)	0.25 (0.22-0.28)***
Other	1,063 (1)	1.04 (0.76-1.44)	428 (1)	2.2 (1.51-3.2)***	329 (1)	0.41 (0.2-0.82)*	306 (1)	1.3 (0.18-9.23)
Otorhinolaryngology	67,646 (7)	0.43 (0.4-0.45)***	19,378 (7)	0.59 (0.53-0.65)***	28,970 (6)	0.39 (0.36-0.43)***	19,298 (7)	0.34 (0.3-0.38)***
Pediatrics	18,177 (2)	0.41 (0.31-0.54)***	8,863 (3)	0.66 (0.44-0.98)*	5,519 (1)	0.28 (0.17-0.47)***	3,795 (1)	0.85 (0.44-1.63)
Physical Med Rehabilitation	10,429 (1)	0.59 (0.53-0.65)***	0 (1)	Not applicable	7,015 (2)	0.53 (0.48-0.6)***	3,414 (1)	0.42 (0.31-0.56)***
Plastic Surgery	1,858 (1)	0.53 (0.43-0.67)***	426 (1)	0.97 (0.63-1.52)	1,432 (1)	0.42 (0.33-0.55)***	0 (1)	Not applicable
Colorectal Surgery	3,114 (1)	0.57 (0.47-0.69)***	0 (1)	Not applicable	328 (1)	0.44 (0.27-0.72)**	2,786 (1)	0.54 (0.44-0.67)***
Psychiatry	13,135 (1)	0.74 (0.65-0.85)***	4,068 (2)	1.24 (0.99-1.54).	6,744 (1)	0.62 (0.51-0.74)***	2,323 (1)	0.66 (0.45-0.97)*
Rheumatology	7,341 (1)	0.4 (0.35-0.47)***	0 (1)	Not applicable	2,898 (1)	0.46 (0.38-0.55)***	4,443 (2)	0.3 (0.25-0.38)***
Sexually Transmitted Disease	1,807 (1)	0.3 (0.17-0.53)***	420 (1)	0.37 (0.09-1.47)	1,250 (1)	0.28 (0.15-0.53)***	137 (1)	0 (0-6.538E+282)
Traumatology	107,111 (11)	0.34 (0.32-0.36)***	33,661 (13)	0.46 (0.41-0.51)***	50,156 (11)	0.3 (0.28-0.32)***	23,294 (9)	0.32 (0.28-0.36)***
Urology	47,102 (5)	0.58 (0.55-0.61)***	19,073 (7)	0.76 (0.69-0.84)***	21,066 (5)	0.54 (0.5-0.58)***	6,963 (3)	0.44 (0.39-0.51)***
Referring Center (Primary C)								
Primary	463,119 (47)		10,180 (4)		283,745 (62)		169,194 (64)	
Secondary	3,455 (1)	0.74 (0.52-1.04)	0 (1)	Not applicable	3,455 (1)	0.74 (0.53-1.05)	0 (1)	Not applicable
Tertiary	685,483 (69)	2.2 (2.14-2.26)***	254,576 (96)	0.59 (0.47-0.73)***	170,728 (37)	2.39 (2.31-2.47)***	260,179 (98)	1.71 (1.63-1.8)***
Accepting Center (Primary C)								
Primary	29,622 (3)		9,359 (4)		15,629 (3)		4,634 (2)	
Secondary	59,672 (6)	Std Dev=0.79	0 (1)	Not applicable	59,672 (13)	2.62 (1.94-3.53)***	0 (1)	Not applicable
Tertiary	898,203 (91)		255,397 (96)	4.95 (3.42-7.16)***	382,627 (84)	3.83 (2.94-4.99)***	260,179 (98)	5.55 (2.26-13.6)***

Abbreviations: N, number of patients; HR, hazard ratio; CI, confidence interval; Std Dev, standard deviation; C, comparator; Med, medicine.

† Results are from Cox proportional hazard models fit by maximum likelihood.

‡ Results are from mixed-effects Cox proportional hazard models with Regional Health Service and Accepting Medical Center included as a crossed random effect.

*** Significant at the 0.1% level, ** significant at the 1% level, * significant at the 5% level.

Appendix B

Here, we provide an example contrasting frameworks A and B in terms of capacity utilization and selfishness. Given that framework A considers the private providers as a back-up system, it is only affected by public selfishness. Conversely, framework B assumes that private providers are part of the negotiations. Therefore, both types of selfishness are included in framework B. Let us assume as an example that the public and private selfishness are equal to 0.4. Figures 13 and 14 provide a sensitivity analysis between selfishness, the percentage of capacity utilized, and the number of transfers in each framework. At selfishness of 0.4, framework A serves 346 patients with a 21.7% capacity utilization, while framework B serves 512 patients with a 23.3% capacity utilization. Despite the favorable results produced by framework B utilizing public and private capacities, framework A provides similar results using exclusively public resources. Suppose the chosen solution of Figure 7 is allowed as an additional expenditure to framework A (enabling the back-up role of private providers). The number of patients served by framework A will then be 1249, surpassing framework B. Given that framework B can have different combinations of public and private selfishness, Table 4 provides some additional scenarios contrasting selfishness, the number of transfers, and the capacity utilization in this framework.

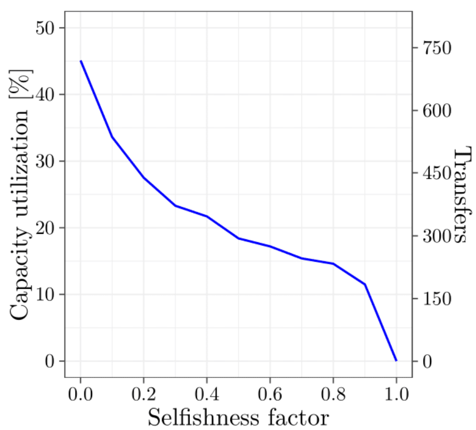

Figure 13: Impact of public selfishness on the capacity utilization and the number of transfers in framework A

Table 4: Examples of the capacity utilization in framework B considering public and private selfishness.

Selfishness		Framework B	
Private	Public	Transfers	Capacity utilization (%)
0.0	0.0	1179	53.7
0.1	0.0	1130	51.5
0.2	0.0	1081	49.2
0.8	0.1	497	22.6
0.9	0.1	543	24.7
1.0	0.1	537	24.5
0.5	0.3	506	23.0
0.6	0.3	421	19.2
0.7	0.3	392	17.9
0.4	0.4	512	23.3
0.5	0.4	463	21.1
0.6	0.4	417	19.0
0.0	0.5	697	31.7
0.1	0.5	655	29.8
0.2	0.5	618	28.1
0.8	0.6	287	13.1
0.9	0.6	300	13.7
1.0	0.6	277	12.6
0.5	0.7	431	19.6
0.6	0.7	360	16.4
0.7	0.7	318	14.5

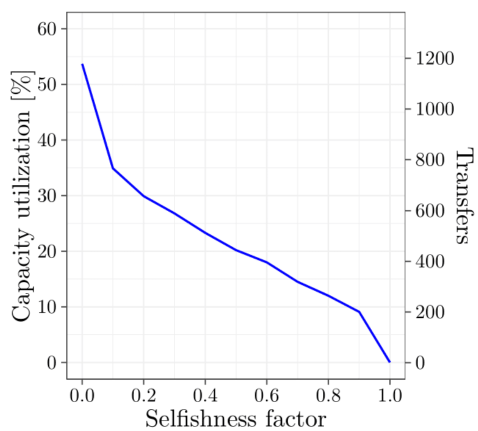

Figure 14: Impact of selfishness on the capacity utilization and the number of transfers in framework B

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Appendix D: Ambulance Allocation Optimization Model for the Overcrowding Problem in US Emergency Departments: A Case Study in Florida

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Ambulance allocation optimization model for the overcrowding problem in US emergency departments: A case study in Florida

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ABSTRACT

In the last decade, emergency department (ED) overcrowding has become a national crisis for the US healthcare system. Increasing mortality rates, decreasing quality of care, financial losses due to walkouts, and ambulance diversion are some of the consequences of ED overcrowding. Given the increasing demand in terms of ambulance utilization, being able to assign service requests to EDs efficiently, becomes a key function of the emergency medical services. This paper presents new ambulance allocation optimization models to reduce patients' total time to treatment, waiting times; therefore, ED overcrowding. Disparities and fairness are considered in the development of the mixed integer programming models. Under a set of assumptions, we apply our strategies to allocate 75 ambulance emergencies to 11 EDs in a specific county in Florida. Heterogeneous types of patients, demand characteristics, and geographical/facility information are considered in the models. Based on numerical experiments and the situation in Florida, we show that the optimization techniques can be utilized for large problems and result in up to 31% improvement of the current decentralized model. Further analysis reveals the negative or positive impact that the strategies have on each patient, giving new insights for future policy modifications. Bi-objective, single objective, and game theory optimization models are implemented in this study.

1. Introduction

Emergency departments (EDs) have traditionally been the places where patients go to receive care in life-threatening situations, or when acute events occur [1]. These health facilities are focused on the care and management of patients who need to be treated within a short period of time. Due to the diverse diseases and conditions treated in an ED, admissions are driven by priority-based policies. Patients may arrive at EDs via special emergency vehicles or on their own (walk-in). These arrivals are not planned or easily predictable, and their stochastic nature impacts the workload and has negative consequences in terms of quality of care and patient waiting time. Therefore, the appropriate assignment of priorities is needed to ensure that each patient receives correct and timely treatment [2,3]. As the United States (US) health care system has evolved under the pressure of political, economic, and clinical matters, the EDs system is being forced to expand their role despite being recognized as the most expensive care [4]. Nowadays, the EDs represent a baseline for the safety net of the health care system regardless of the economic or social status of patients [5]. From the 145 million of patients attending US EDs annually, over 12 million are uninsured [6]. Additionally, EDs have taken on the responsibilities of public health surveillance, disaster preparedness, caring for indigent people, and primary care due to barriers to access at this level of care [7,8]. In 2016 the number of annual ED visits per 1000 habitants reached 441 emergencies [9]. Despite the increase in demand for and utilization of emergency services, the number of EDs in the US, along with the total number of hospitals and hospital beds, have decreased significantly in the last two decades [10,11]. As a consequence, the ability of emergency teams and physicians to deliver adequate care is affected [12]. The disproportion between supply and demand, caused by the factors stated above, has led to the national crisis of overcrowding [5,13,14].

Although there is no agreement on an exact definition of ED overcrowding, it often refers to an overburden of patients in treatment areas that exceeds the ED resources capacity, frequently requiring that medical care be provided in ED corridors and other temporary examination areas [15]. A national US survey showed that more than 90% of large hospitals have their EDs operating at or over capacity [13]. Overcrowding has been associated with long waiting times, especially for patients who are not critically ill, thus decreasing the quality of care; increasing mortality; increasing patient walkouts; increasing ambulance offload delays; and increasing ambulance diversion among other externalities [16–18].

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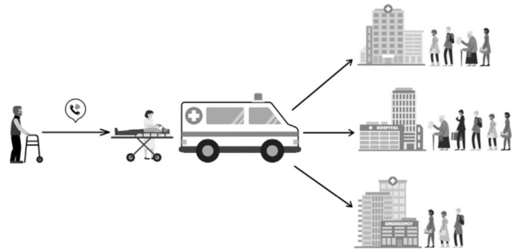

Fig. 1. Standard system process.

In addition to the impact perceived by the patients, hospitals are facing financial losses due to walkouts and ambulance diversion as consequences of overcrowding in EDs. Researchers have found that there is a revenue loss of USD 3.9 million per year for a 500-bed hospital [19]. According to the National Hospital Ambulatory Medical Care Survey, between 2003 and 2015 the number of emergency patients who arrived at EDs via ambulances increased from approximately 16 million to 21 million per year in the US [20,21]. In this context, the allocation of service requests to EDs plays an essential role in overcrowding, not only in terms of life-threatening scenarios but also from a financial perspective.

1.1. Problem description

In the US, emergency medical services (EMS) refers to the treatment and transport of injured or sick patients to hospitals. Despite the tremendous importance of the system, the lack of strong representation at the federal level and the increasing number of local agencies and system models make a fully encompassing definition impossible [22, 23]. There are more than 21,000 licensed local EMS agencies in the US that can be classified into three main groups according to the tasks they perform: (1) Agencies that focus primarily on 911-based emergencies with or without transport; (2) EMS that provide scheduled medical transport; and (3) EMS that provide emergent inter-facility transport [24]. In this study, we focus on the first category with transport, particularly the utilization of ambulances. Fig. 1 shows the most common process patients go through. The steps include calling 911 to request help, receiving initial treatment by the ambulance personnel, and choosing the destination ED. Across the US, different protocols are followed in determining the destination ED. The different states and counties customize their policies. For example, Hillsborough County in Florida gives the responsibility of determining the most appropriate facility to the senior caregiver at the scene. He or she has to decide the final destination in accordance with the state-approved Hillsborough County Trauma Agency Plan. Basically, a patient is transported to the chronological/developmental, age-appropriate, treatment facility [25]. It is necessary to add other elements to these customized protocols, which can lead to the inefficient allocation of service requests to EDs. For example, Medicare only covers ambulance service to the nearest appropriate medical facility that can provide the care [26], and some private insurances cover medical transportation only if the ambulance company is a partner organization or the provider is part of the network. Additionally, the large number of ambulance providers by area (e.g., county) is a barrier to coordination with EDs.

Several studies have been conducted in the framework of EMS planning and facility allocation. In this paper, we divided the literature into two main pillars. The first considers publications related to ambulance assignment to call request, dispatch policies, and allocation of EMS to increase coverage. This pillar has been widely studied in the last decade; from these research efforts, many publications have emerged. [27–35]. We are interested in the second pillar, which focuses on the allocation of medical emergency service requests to ED, the decision that pairs ambulance emergencies and hospitals' ED. The following are publications that provide interesting results and understanding of the different techniques available for the allocation of services request to ED or similar problems.

In [36], through queuing theory, the interface between regional EMS provider and EDs serving ambulances and walk-ins was modeled. Markov chain was utilized to analyze the ambulance offload delays due to overcrowding in EDs. A simulation was implemented to validate the model assumptions. In [37], a stylized queuing model with blocking was used to analyze the effect of routing decisions on EMS and to help in creating proper patient allocation policies for multiple hospitals in a region. [38] used mixed integer programming (MIP) to optimize the allocation of ambulance request to EDs, considering geographical information in a region of Italy. A complete offline picture of an optimal assignment was used to evaluate the price of anarchy, where centralized allocation is useful as a reference for the state of the art of the decentralized approach and future reorganization ideas. In [39], through a queuing game between two EDs that minimizes the waiting time, it was found that the decentralized decisions related to diversion generated a lack of pooling benefits. The existence of a defensive equilibrium was also discovered. Additionally, the benefits of a centralized planner that maximizes the social optimum in terms of diversions were estimated. In [40], approximate dynamic programming optimization was utilized to reallocate ambulances after first-aid requests to the waiting location in a time-efficient manner. In [41], a design of pragmatic retrospective cohort analysis of all the planned and unplanned ED visits was studied. The planned visits followed an ambulance service secondary telephone triage, and the impact on ED admissions was measured. The study shows that planned visits were more likely to be admitted to hospital and to find a suitable ED, compared to emergencies that were not planned ED visits. [42] studied proactive destination selection considering real-time data of the regional EMS system. The authors showed that proactive destination selection could improve regional capacity and helps to reduce ambulance diversions. [43] implements a "nurse navigator program" to identify the ideal destination ED between two nearby hospitals. The improvement of load-balancing considered real-time information from EDs that is utilized to inform the EMS. The article showed that a proactive mechanism of nurse navigator with real-time data could decrease EMS turnaround time.

Our contribution: In the present work, we investigate the overcrowding problem from the viewpoint of the allocation of emergency requests to EDs in the US system. Three optimization strategies are proposed, taking into account both the EDs' workloads and service allocation. We consider remote triage management, as suggested by [38]. That is, anticipating patient priority can help in handling emergency requests to EDs, thus assuring the best possible service level.

Unlike previous approaches, we recognize the fact that minimizing total or average time across all emergencies, may favor certain patients over others. This is a common problem in optimization models focused on efficiency-based objectives [44]. By incorporating terms of fairness and disparities, we aim to provide patient-centered solutions that recognize the necessity of improving efficiency in the context for which they are designed.

When working on healthcare systems, there is an imperative need to acknowledge the issues previously described. Prioritizing the common welfare of the community over individual patients implies potential loss of lives. This situation may be disregarded in other fields, where the thing being optimized is inert, or the externalities only have an economic impact.

The first strategy that we propose focuses on system efficiency and is modeled using MIP with a single objective function. Our second strategy focuses on the reduction of disparities, and the Min–max technique is used to develop a bi-objective MIP problem. Finally, the

Table 1
Model indices.

Symbol	Definition
i	Emergency in the system, where $i \in I$.
j	Emergency department in the system, where $j \in J$.
t	Period of time, where $t \in T$.
p	Pathology, where $p \in P$.

integration of game theory and MIP enabled us to generate a grand coalition between our objectives/imaginary players to improve the efficiency of the system and provide fair payoffs to the patients. A non-symmetric bargaining game is utilized in this last strategy.

While each strategy improves the current decentralized system, we analyze and discuss the differences among them. Total waiting times, fairness, and efficiency are some of the critical points under analysis. These strategies represent potential guidelines to modify policies, increase service capacity, and reduce overcrowding in EDs.

1.2. Structure

The following section describes the notation and definitions for the mathematical representation of the system. Section 3 covers the formulation of the problem and presents the required modifications of each strategy under analysis. In Section 4, the formulation is tested through a numerical experiment. Section 5 presents a case study in Florida, where the strategies are applied. Finally, Section 6 comprises the conclusion and future research directions.

2. Notation and definitions

We modeled the time horizon of the system using a discrete ordered set $T = 1, \ldots, t$. Each element of the set represents a period of time when emergencies may occur, and decisions need to make. Let I be the set of emergencies that need to be assigned to EDs in the time horizon T. G denotes the set of areas in which the region under analysis is divided. Let U represent a subset of areas G where the hospitals' EDs are located. The set of hospitals' EDs in the region is defined by J. Finally, let P and C represent the set of pathologies and priority codes, respectively.

Similar to the work done in [38], each emergency i is modeled by a quadruple (g_i, ψ_i, c_i, p_i), where $g_i \in G$ represent the location of emergency i, $\psi_i \in T$ is the time period in which the emergency i occurs, $c_i \in C$ is the priority code assigned by the ambulance personnel to i, and $p_i \in P$ is the pathology associated with i.

Every ED j is also modeled by a quadruple $(u_j, w_j^t, \sigma_{pj}, q_{pj})$, where $u_j \in U$ represents the location of ED j. w_j^t is the waiting time in ED j at period t, which depends on the number of ambulance emergencies assigned to j, as well as walk-ins and patients already waiting at j. The capability of the ED j to treat the pathologies is defined by a binary parameter σ_{pj}, where $p \in P$. Finally, the quality of treatment that ED j can provide for a given pathology p is denoted by q_{pj}.

Tables 1–3 summarize all indices, parameters, and variables required for the mathematical formulations.

3. Mathematical formulation and strategies

This section introduces the model formulation of the problem and describes the modifications required for each strategy.

Table 2
Model parameters.

Symbol	Definition
c_i	The priority code assigned to the emergency i.
d_{ij}	The travel time of emergency i to arrive at ED j.
q_{pj}	The quality of care for pathology p offered by ED j.
φ_j	The initial number of patients waiting at ED j.
l_j^t	The number of walk-in patients at ED j in time period t.
α_j^t	The proportion of patients still waiting to be treated in j and period t.
σ_{pj}	Binary parameter, 1 if ED j can treat pathology p, 0 otherwise.
δ_i^t	Binary parameter, 1 if emergency i occurs in period t, 0 otherwise.
ψ_i	Time period in which emergency i occurs.
w_{max}	The maximum waiting time before starting ambulance diversion.
β	The minimum quality of care expected for every patient.
a_j	Slope coefficient of the waiting time function in j.
b_j	Intercept coefficient of the waiting time function in j.
r_i	Binary parameter, 1 if i is traveling more than 15 min, 0 otherwise.
θ_i	Time to treatment for i without the creation of coalition (status quo).
np	Number of players in the bargaining game.

Table 3
Model variables.

Symbol	Definition
x_{ij}	1 if patient i is assigned to ED j, 0 otherwise.
w_j^t	Waiting time at ED j in time period t.
n_j^t	Total number of patients being assigned to ED j in time period t.
z_j^t	1 if ED j in time period t is not doing diversion, 0 otherwise.
v_{ij}	Total time that emergency i waits to receive treatment if assigned to ED j.
λ_{c_i}	Maximum time that i with priority code c_i has to wait for treatment.
y_i	Expected time to treatment of i.
$\hat{y}_{if}$	Expected time to treatment of i and his/her f copies.

3.1. Mixed-integer programming formulation

To describe the MIP formulation, which is the core of our strategies, we introduce the basic constraints.

- Constraint (1) ensures that each emergency is assigned to one ED among all periods.

$$\sum_{j \in J} x_{ij} = 1 \qquad \forall i \in I \tag{1}$$

- Constraint (2) captures the total number of emergencies assigned to a particular ED j in a time period t.

$$\sum_{i \in I} x_{ij}\delta_i^t = n_j^t \qquad \forall j \in J \quad \forall t \in T \tag{2}$$

- Constraint (3) initializes the variable n_j^t in period $t = 0$.

$$n_j^0 = \varphi_j \qquad \forall j \in J \tag{3}$$

- Constraint (4) represents the function of waiting time at each ED j for a given period t. Different studies have been performed to understand the relationship between ED waiting time and its occupancy levels [45–47]. In [38], the authors showed, through the analysis of historical data, that the average waiting time can

be expressed as a convex piecewise linear function of occupancy levels. Based on this contribution and for simplicity, we assumed the waiting time of each ED as a linear function of their workload in a given period t. This function considers the arrival of emergencies through ambulances and walk-ins in the current period, furthermore, incorporates the patients from previous periods still waiting for treatment at ED j. For more information regarding convex piecewise linear functions, we refer the readers to [48].

$$w_j^t = a_j[\alpha_j^t(n_j^{t-1} + l_j^{t-1}) + n_j^t + l_j^t] + b_j \quad \forall j \in J \quad \forall t \in T \tag{4}$$

- In (5), we ensure that if ED j cannot treat pathology p, emergency i is not assigned to j.

$$x_{ij} \leq \sigma_{p_i j} \qquad \forall i \in I \quad \forall j \in J \tag{5}$$

- (6) defines the threshold of maximum waiting time before ambulance diversion across all EDs. M represents a large value (e.g., the value of the worst scenario for any ED in terms of waiting time) and z_j^t is a binary variable equal to one if $w_j^t \leq w_{max}$, and zero otherwise.

$$w_j^t \leq w_{max} + M(1 - z_j^t) \quad \forall j \in J \quad \forall t \in T \tag{6}$$

- Constraint (7) generates the diversion of emergencies if ED j exceeds the maximum waiting time threshold.

$$x_{ij} \leq z_j^t \quad \forall i \in I \quad \forall j \in J \quad t = \psi_i \tag{7}$$

- (8)–(11) define the range and type of variables.

$$x_{ij} \in \{0, 1\} \quad \forall i \in I \quad \forall j \in J \tag{8}$$

$$n_j^t \in \mathbb{Z}^+ \quad \forall j \in J \quad \forall t \in T \tag{9}$$

$$w_j^t \in \mathbb{R}^+ \quad \forall j \in J \quad \forall t \in T \tag{10}$$

$$z_j^t \in \{0, 1\} \quad \forall j \in J \quad \forall t \in T \tag{11}$$

3.2. Strategy 1: System efficiency

Our first strategy aims to reduce the total time that emergencies have to wait to be treated and to minimize the transfer and waiting time at EDs for all emergencies. To give preference to the patients in the worst condition, we use an emergency priority code as a weight in each summation of the objective function. This approach, based on maximizing overall system efficiency, is similar to the work done in [38–40].

The following problem provided the general formulation of strategy 1.

Problem 1.

$$\min \sum_{i \in I} \sum_{j \in J} \sum_{t \in T} c_i(d_{ij} + w_j^t) x_{ij} \delta_i^t \tag{12}$$

$$\max \sum_{i \in I} \sum_{j \in J} q_{p_i j} x_{ij} \tag{13}$$

subject to (1)–(11)

In Problem 1, the first objective function (12) minimizes the summation of times, where for each patient the travel time and the waiting time at the ED are multiplied by the corresponding priority code. At the same time, the second objective function (13) maximizes the summation of the quality of care that patients receive. This last objective cannot be easily added to the previous function because the parameter to transform quality into time is unknown and difficult to estimate. However, the second objective function can be turned into a constraint to facilitate calculations.

From Problem 1, we can notice that the first objective function (12) is non-linear. Therefore, we next describe the linearization; four new constraints are added, and the objective function is modified.

- Constraint (14) defines a new variable that is smaller or equal to the sum of the travel and waiting times.

$$v_{ij} \leq d_{ij} + w_j^t \quad \forall i \in I \quad \forall j \in J \quad t = \psi_i \tag{14}$$

- Constraint (15) forces the new variable for total time to be zero if the binary variable x_{ij} is equal to zero. Basically, the time to treatment in ED j for emergency i cannot exist if the patient is not assigned to that ED. When x_{ij} is equal to one, the value of M has to be large enough to ensure that the variable v_{ij} is smaller or equal to the sum of the travel and waiting times.

$$v_{ij} \leq M x_{ij} \quad \forall i \in I \quad \forall j \in J \tag{15}$$

- If variable x_{ij} is equal to one, then constraint (16) combined with (15) makes the new time variable v_{ij} equal to the sum of the travel and waiting times.

$$v_{ij} \geq d_{ij} + w_j^t - M(1 - x_{ij}) \quad \forall i \in I \quad \forall j \in J \quad t = \psi_i \tag{16}$$

- Constraint (17) defines the range and the type of variable to v_{ij}^t.

$$v_{ij} \in \mathbb{R}^+ \quad \forall i \in I \quad \forall j \in J \tag{17}$$

In Appendix A, we further discussed how the linearization procedure applied to constraints (14)–(17) works, including a reference that provides additional insights about this topic.

The next step converts the objective function (13) into a constraint. This transformation helps to solve larger instances of the problems and in a shorter period of time. This is a common advantage of models with a single objective function versus bi-objective models [49]. However, proper knowledge about the minimum level of quality expected for every patient is required; an incorrect value may make the problem infeasible.

- Constraint (18) sets a minimum level of quality of care for every patient. Parameter β is used as the lower bound.

$$\sum_{j \in J} q_{p_i j} x_{ij} \geq \beta \quad \forall i \in I \tag{18}$$

With the previous constraints and modifications added to the model, the new problem for strategy 1 is:

Problem 2.

$$\min \sum_{i \in I} \sum_{j \in J} c_i v_{ij} \tag{19}$$

subject to (1)–(11) and (14)–(18)

In Problem 2, the objective function (12) is replaced by objective function (19). The main advantage is the change from a non-linear to a linear function that can be easily managed with commercial solvers. Additionally, the objective function (13) is converted into a constraint to speed up the processing time of the solver.

Consequently, using Problem 2, we can solve the first strategy to improve the allocation of service requests to EDs. It is important to notice that constraints (14) and (15) can be ignored due to the minimization characteristic of the problem.

As mentioned in the previous section, the approach described for strategy one is based on optimizing an efficiency-based objective. The development of the next two strategies is founded on the necessity of finding fair approaches to improve the system.

3.3. Strategy 2: Min–max on disparities

In our second strategy, we implemented the min–max technique to reduce disparities [49]. Given that the literature on healthcare shows the existence of vast inequality in access to care between rural and urban areas [50], we focus our approach on patients traveling more than 15 min to EDs. Previous models in the literature do not consider that patients with the same severity of illness, but distinct travel times should be prioritized differently in EDs.

A new objective function has to be added to the model in strategy one to generate a non-dominated frontier between the system efficiency and the reduction of disparities. In a bi-objective problem, the non-dominated frontier is defined as the set of feasible solutions in the criterion space that cannot be improved in the value of one objective without worsening the other [51].

Problem 3.

$$\min \sum_{i\in I}\sum_{j\in J} c_i v_{ij} \tag{19}$$

$$\min \sum_{i\in I} \lambda_{c_i} r_i \tag{20}$$

subject to (1)–(11), (14)–(18), and

$$v_{ij} r_i \le \lambda_{c_i} \quad \forall i \in I \quad \forall j \in J \tag{21}$$

Problem 3 presents the formulation required in strategy 2. The objective function (20) minimizes the sum of maximum times by priority class. Only emergencies with travel time longer than 15 min are considered in this objective. Using independent time variables by priority class helps to develop different upper bounds by type of patient. Constraint (21) sets the time limit for emergencies with travel time longer than 15 min. Finally, the model for the min–max on disparities considers objective functions (19), (20), and constraints from (1)–(11), (14)–(18) and (21) as presented in Problem 3.

Strategy two generates a non-dominated frontier of solutions, where each solution has components of efficiency and fairness. The fact that a non-dominated frontier is created in the criterion space (space of objective function values) is directly related to the trade-off existing between the two components. In other words, the improvement of one component can be obtained only at the expense of the deterioration of the other component [49].

3.4. Strategy 3: Game theory and cooperative model

In our last strategy, we implement a non-symmetric version of the two-player cooperative games from [52,53], also known as the non-symmetric bargaining games. A bargaining problem is a cooperative game where the players create a grand coalition instead of competing with each other to get better payoffs [50].

Two important axioms relating to bargaining games are individual rationality and Pareto optimality. The first one establishes that no player will accept a payoff lower than the one under disagreement. In our problem, this axiom represents the patients who, based on their total current time, are not willing to accept a longer total time. The second axiom introduces the trade-off among the players when a solution has been obtained. Thus, the solution guarantees that the total time for one patient cannot be decreased without negatively affecting the total times of other patients. It is noted that in practice patients do not negotiate; however, the model pretends that they do to safeguard the interest of each patient while improving overall efficiency.

In the allocation of ambulance request to EDs, the patients or emergencies represent the players, and the time to treatment is the payoff they received. To model the bargaining game, non-symmetric powers are needed to represent the priority codes of the emergencies. Therefore, the priority of each emergency is the capacity of the player to influence the negotiation to obtain a better time or payoff.

The objective function (22) maximizes the differences between the status quo or disagreement and the expected times obtained through the new coalition for more than two players. The priority code c_i gives different negotiation power to the players depending on the emergency condition.

$$\max \prod_{i\in I} (\theta_i - y_i)^{c_i} \tag{22}$$

We next present the basic formulation of strategy 3.

Problem 4.

$$\max \prod_{i\in I}\prod_{f=1}^{c_i} (\theta_i - \hat{y}_{if}) \tag{23}$$

subject to (1)–(11), (14)–(18), and

$$y_i = \sum_{j\in J} v_{ij} \quad \forall i \in I \tag{24}$$

$$y_i = \hat{y}_{if} \quad \forall i \in I \quad \forall f = 1, \dots, c_i \tag{25}$$

$$y_i \le \theta_i \quad \forall i \in I \tag{26}$$

In Problem 4, the objective function (23) is the transformation of the objective function (22) into the standard Nash optimization problem. c_i copies are created for each patient, increasing the number of players artificially. Constraint (24) is added to match the value of the expected time to treatment y_i with the value of the variable v_{ij}. Meanwhile, constraint (25) guarantees that the copies of the expected time to treatment have the right value. Finally, in (26), the axiom of individual rationality is established; the patients only accept payoff greater or equal to the status of disagreement.

As can be observed, the objective function (23) has to be linearized. Because the variables are not binaries, a special reformulation is necessary. The second-order cone problem (SOCP) can be used to reformulate this model and has the advantage that commercial solvers can solve it. Basically, a new non-negative variable γ and a geometric constraint are added to the model. To avoid computational issues with the geometric constraint, a final reformulation is presented in Problem 5. This last model replaces the geometric constraint with a set of non-negative variables and constraints.

Next, we show the mathematical reformulation of SOCP. The objective function (27) and the constraints (28)–(32) are introduced to our model. Let κ be the smallest integer value such that $2^\kappa \ge np$. The set of non-negative variables Γ and τ are generated for the mathematical transformation of Problem 4; accordingly, they do not have an explicit meaning for our model.

Problem 5.

$$\max \gamma \tag{27}$$

subject to (1)–(11), (14)–(18), (24)–(26), and

$$0 \le \gamma \le \Gamma \tag{28}$$

$$0 \le \Gamma \le \sqrt{\tau_1^{\kappa-1}\tau_2^{\kappa-1}} \tag{29}$$

$$0 \le \tau_j^l \le \sqrt{\tau_{2j-1}^{l-1}\tau_{2j}^{l-1}} \quad \forall i = 1, \dots, 2^{\kappa-l} \quad \forall l = 1, \dots, \kappa - 1 \tag{30}$$

$$0 \le \tau_j^0 = \theta_j - \hat{y}_j \quad \forall j = 1, \dots, np \tag{31}$$

$$0 \le \tau_j^0 = \Gamma \quad \forall j = np + 1, \dots, 2^\kappa \tag{32}$$

Finally, the strategy of the cooperative model has to consider objective function (27) and constraints (1)–(11), (14)–(18), (24)–(26), and (28)–(32) to solve the allocation of ambulance request to EDs. As established by the second axiom, the solution obtained guarantees the trade-off among players. A unique solution can be found in the non-symmetric bargaining game.

4. Numerical experiment

This section introduces the numerical experiment of our strategies. Different random instances are run to verify the size of problems that can be solved by our formulations. Strategy one is selected to run the analysis, given that its formulation is utilized by strategies two and three. Additionally, it is the fastest model to solve due to the single objective function. The model is implemented in Julia language and uses Gurobi 7.5.2 as the MIP solver. The experiments are conducted on a Dell OptiPlex 5040 with an Intel(R) Core(TM) i7-6700U @ CPU 3.40 GHz, 16 GB RAM, with a 64-bit operating system, Windows 10 Pro.

We performed all instances based on simulated data for both patients' conditions and EDs' characteristics. The random values are obtained based on the case study presented later. The maximum waiting time is fixed at 120 min, the minimum quality of care at 70%, and the value of big M at 200. See Appendix B for more information regarding the data utilized in this section. In our problem, big M should take the value of the worst scenario for any ED in terms of waiting time. The value of big M has to be carefully calculated to improve the performance.

Six classes are defined to run the computational study. The first index of a class represents the number of emergencies, and the second represents the number of EDs. Table 4 shows the results of 30 random instances and their respective averages by class. As can be observed, classes 50–100, 80–15, 100–15, and 100–20 are solved to optimality with 0% gap, while classes 150–20 and 200–30 show gap values greater than 0%. The time required to solve the first four classes is less than a minute, which we associated with a good capacity of the formulation to solve medium and large size problems to optimality.

Because instances with 150 or more patients and 20 or more EDs are not solved in a reasonable period of time, we have limited the solver elapsed time to three minutes. The same instances are shown in Table 5, but in this case, the solver is limited to one hour. These two settings show the performance deterioration of the formulation as classes increase in size. The solver takes three minutes to obtain the 10.22% and 11.14% average optimality gap, respectively. The gap is reduced to 8.60% for class 150–20 and 9.19% for class 200–30 after one hour running, which is equivalent to less than one minute improvement in the average mean time to treatment. Therefore, the time effort cannot be justified through a real improvement of the solution, and the deterioration of the solver becomes evident.

When looking to the number of variables presented in Table 4, we see the complexity of the problem under analysis, and the thousands of possible interactions that need to be considered when handling the allocation of emergency requests to EDs.

The following section introduces the analysis for a real scenario, where the three strategies are implemented.

5. Case study

This section presents a case study based on the context of Hillsborough County (Florida) in the United States. Hillsborough County has a population of 1.4 million of habitants and covers an area of 1,266 square miles in the state of Florida. The case uses the Healthcare Cost and Utilization Project (HCUP) databases for the state of Florida of the year 2014. We combined the State Emergency Department Databases (SEDD) [54], with the State Inpatient Databases (SID) [55]. The first database covers all ED visits per state that did not result in an admission, while the second, includes 97% of all the discharges in the community hospitals across the United States. Based on the Five Year Trauma Plan Update of Hillsborough County [56], there are two trauma and nine non-trauma centers that meet the criteria of receiving centers for emergency stabilization. These eleven emergency departments were selected from the Florida State HCUP database to conduct the analysis.

Considering the national percentage of arrivals to EDs through ambulances (14%) [57] and the HCUP database, we estimated that 150 ambulance emergencies and 900 walk-ins are received daily in the EDs of Hillsborough County. Reports [6,58] were utilized to collect data related to the priority code assigned to each emergency. We used the information provided in [59] as the source for the quality of care by type of pathology and the hospitals' EDs capability to provide treatment. We considered seven official subdivisions of the county (Brandon, Keystone, Palm River, Plant City, Ruskin, Tampa, and Wimauma-Riverview) [60] where emergencies may occur and the six diagnoses with the higher frequency in the HCUP databases (chest pain, complication of pregnancy, respiratory infections, headache, abdominal pain, and urinary tract infections). Combining the data available in Hillsborough County GeoHub [61] and the software ArcGIS Desktop 10.5, a geographical representation of the county was made. Fig. 2(a) shows the location of the EDs and county subdivisions with different layers. Fig. 2(b) presents in gray the high-density population areas by zip code. Based on the locations of the EDs and county subdivisions, the travel time was estimated in a range of plausible values. Considering the population levels [62], the number of emergencies per area was assigned. Using R software 3.6.1 and the HCUP database, we fitted a linear regression for each ED to estimate the parameter a_j of the waiting time function (average adjusted R-squared of 0.937). At zero occupancy the waiting time in the EDs is zero; therefore, the intercept b_j of each function is zero. The 2018 Florida Statues [63] gives hospitals the opportunity to develop emergency room diversion programs but do not specify standards. The State of Florida, in a reassessment of EMS document from 2013, points out the necessity of matching system resources with patient needs in developing diversion policies [64]. Given that the national average waiting time in EDs is around 58 min [65], we established a maximum waiting time of 150 min before diversion. Basically, no patient should wait more than 2.5 times the national average. This setting is used for our three strategies and the current decentralized model. An instance with 75 ambulance emergencies, 450 walk-ins, and 11 EDs, which approximates half a day of service demand and resources in Hillsborough County, was applied to our models. For simplicity, we considered a 12-hour time frame and divided it evenly in 12 periods. The literature shows that different levels of priorities have been studied in EDs [66,67]. We considered a five-level triage system as described by the National Hospital Ambulatory Medical Care Survey (non-urgent, semi-urgent, urgent, emergent, and immediate) [6]. Notice that the models developed can consider different number of areas, periods, and pathologies in accordance to the context under analysis. The minimum quality of care was fixed at 70% based on the national average percentage of patients receiving recommended acute care [68].

The bi-objective model for the min–max on disparities is solved using the perpendicular search method [69,70]. The perpendicular search method utilizes a search direction that is always perpendicular to the parameter axis. The last implies that one parameter at a time changes, while all other parameters keep the same value. After one step, the next parameter is employed, and the process continues [71].

5.1. Results

This section provides graphical views of the results. The emergencies are sorted based on the total time to treatment on the decentralized model in increasing order. Fig. 3 presents the results for total time to treatment of each emergency in the current/decentralized model and strategy one (efficiency model). The horizontal axis shows the emergencies, and the vertical axis shows the total time to treatment

Table 4
Numerical results, part I.

Class	Objective value	Mean time to treatment (min)	Mean travel time (min)	Mean waiting time (min)	Time running (s)	Primal–Dual gap (%)	No. of variables
50–10	1717	52	14	38	0.04	0	1200
	1546	49	15	34	0.09	0	1200
	1948	64	13	51	0.11	0	1200
	1542	56	13	43	0.05	0	1200
	2329	79	12	67	0.40	0	1200
Average	1816	59	14	47	0.138	0	1200
80–15	2380	50	11	38	1.33	0	2705
	2542	51	14	37	2.77	0	2505
	2537	51	13	38	1.06	0	2505
	2706	52	13	39	1.52	0	2505
	2622	54	13	41	0.31	0	2505
Average	2557	52	13	39	1.39	0	2505
100–15	3511	56	13	43	1.71	0	3325
	3103	50	12	37	3.42	0	3325
	3612	55	13	41	3.87	0	3325
	3135	54	12	42	1.51	0	3325
	3373	50	13	36	5.35	0	3325
Average	3347	53	13	40	3.17	0	3325
100–20	3121	49	13	36	2.88	0	4400
	2786	42	11	31	19.03	0	4400
	3014	48	13	35	6.47	0	4400
	3057	48	12	36	34.33	0	4400
	2607	45	14	31	2.87	0	4400
Average	2917	46	12	34	13.11	0	4400
150–20	5184	55	13	42	180	4.55	6450
	4268	50	12	37	180	11.87	6450
	4682	49	12	36	180	12.19	6450
	5340	56	12	43	180	10.21	6450
	4734	50	13	37	180	12.30	6450
Average	4842	52	12	39	180	10.22	6450
200–30	6004	47	11	36	180	6.00	12650
	5120	43	12	31	180	14.16	12650
	7290	51	11	39	180	8.03	12650
	5727	43	11	32	180	10.65	12650
	5874	47	12	35	180	16.86	12650
Average	6003	46	11	35	180	11.14	12650

Table 5
Numerical results, part II.

Class	Objective value	Mean time to treatment (min)	Mean travel time (min)	Mean waiting time (min)	Time running (s)	Primal–Dual gap (%)	No. of variables
150–20	5183	55	13	42	3600	4.38	6450
	4255	50	12	38	3600	10.04	6450
	4652	48	12	37	3600	10.36	6450
	5337	56	13	43	3600	8.65	6450
	4725	50	13	37	3600	9.55	6450
Average	4830	52	13	39	3600	8.60	6450
200–30	5997	47	11	36	3600	5.00	12650
	5063	43	11	31	3600	11.86	12650
	7280	51	12	39	3600	6.62	12650
	5694	43	11	32	3600	9.35	12650
	5783	47	12	35	3600	13.14	12650
Average	5963	46	11	35	3600	9.19	12650

in minutes. In a decentralized model, the emergencies are assigned to the closest ED that can treat the patients properly. The results obtained using the model mentioned above are fundamental to contrast with the proposed strategies. As can be observed, in the efficiency strategy, the values of total time to treatment of most patients are reduced significantly compared to the decentralized model. However, another small group of emergencies received a negative impact on its times to treatment, particularly, emergency 1, 19, 20, 26, and 27. This last group may represent the favoring of the common good over the welfare of some patients. We analyze the possible implications of this strategy later.

In Fig. 4, the non-dominated frontier for the bi-objective problem is shown. For the min–max strategy, the trade-off between efficiency (horizontal axis) and fairness (vertical axis) is created. With this technique, the decision-maker can choose a particular solution according to the necessities of the system. Objectives one and two of Fig. 4 are functions of time; therefore, the smaller the value of the objective is, the better the efficiency and fairness of the system are, respectively.

Fig. 5 shows the results when comparing strategy two and the current model. A similar analysis to Fig. 3 can be done in this comparison, where a group is affected positively by the min–max strategy and another smaller group negatively. The values of the min–max are obtained when the point (6944, 4244) is chosen from the non-dominated frontier. These objective values provide the solution with the highest level of fairness and the lowest level of efficiency that the min–max strategy can generate. Therefore, the solution of point (6944, 4244) shows the best contrast when compared with the efficiency strategy solution. These changes are analyzed in detail in Figs. 7 and 8. See Appendix C for more information related to solutions to other points in the non-dominated frontier.

Fig. 6 shows the results of our last strategy versus the current decentralized model. One of the main advantages of the non-symmetric

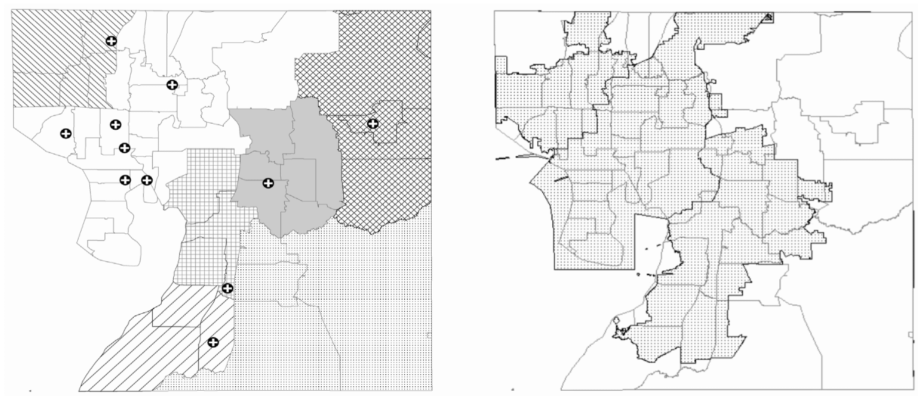

Fig. 2. Hillsborough County.

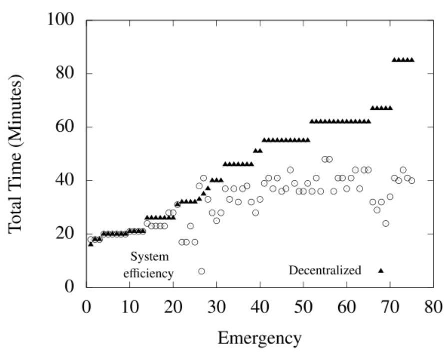

Fig. 3. Total times, decentralized vs. system efficiency.

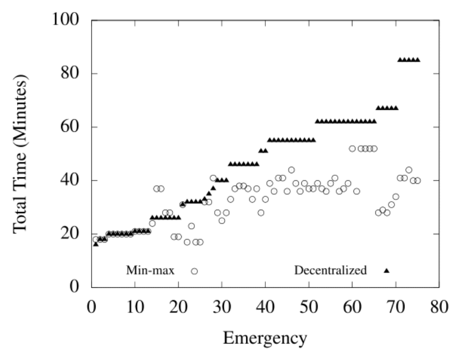

Fig. 5. Total times, decentralized vs. min–max.

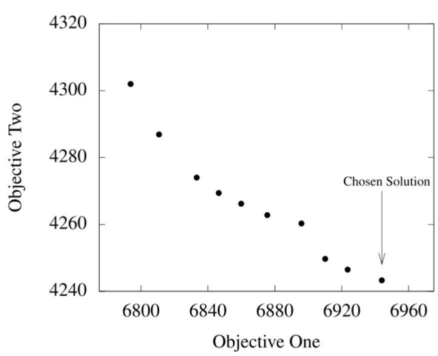

Fig. 4. Min–max non-dominated frontier.

bargaining strategy is that it results in a fair improvement for patients and not just for the system. In this case, all the observations of strategy three have their times located at the same or under the decentralized conditions, ensuring that only positive impacts in emergencies are allowed. Figs. 7 and 8 present a comparison between the efficiency and min–max strategy when the point (6944, 4244) is chosen from the non-dominated frontier. Fig. 7 shows the emergencies for which the travel time exceeded 15-minute threshold. Those observations in which the travel time is the longest for the first strategy are reduced by the min–max. As mentioned in previous sections, the min–max imposes an upper bound of travel time by priority code class. Therefore, as much we decrease the disparities of the system, more observations with travel time greater than 15 min have their total time to treatment reduced.

From Fig. 8, we can observe the negative impact that patients with a travel time less than or equal to 15 min experienced due to the fairness strategy. Given that the trade-off existing between fairness and efficiency represented in the non-dominated frontier is not a one-to-one relationship, to decrease one unit of time for a patient in an unfair situation, more than one unit of time has to be given up for another patient. Therefore, in general, the distance between the triangles and the circles is longer in Fig. 8 than in Fig. 7. The gap may be reduced depending on the solution chosen by the decision-maker.

Table 6 summarizes some statistics of the decentralized model and the proposed strategies. Average travel, waiting, and total time are presented. The improvement row shows in minutes and percentage the difference in terms of total time to treatment between the current model and each of the strategies. Therefore, these numbers represent earnings

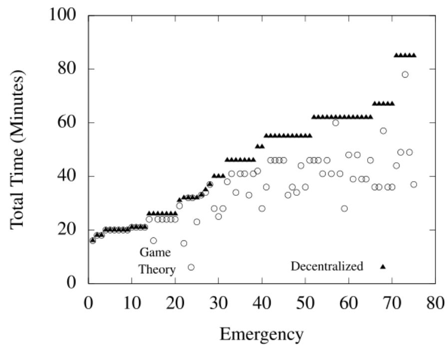

Fig. 6. Total times, decentralized vs. game theory.

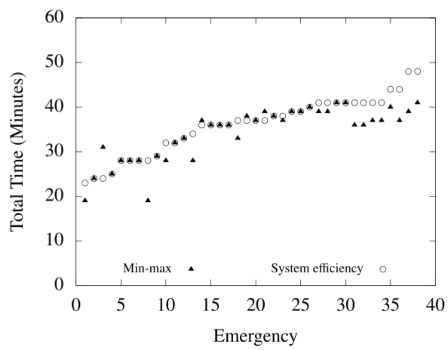

Fig. 7. Emergencies with travel time longer than 15 minutes.

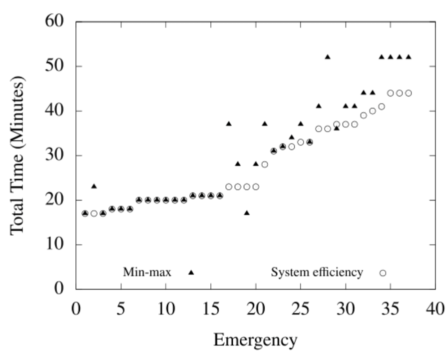

Fig. 8. Emergencies with travel time equal to or less than 15 minutes.

for the system in terms of time. The results of average total time and standard deviation indicate that the efficiency and min–max strategy, provide a substantial improvement to the current system. Nevertheless, the fact of patients being affected negatively in favor of the common good needs further analysis. Additionally, the results of the min–max strategy depend on the chosen solution in the non-dominated frontier. In the case of the game strategy, the overall system improvement is not as good as in the previous two models but guarantees non-negative results for each emergency. However, how the status quo is defined impacts the results. In our case, the status quo was considered as the decentralized model. Based on the conditions of the current model, we use Fig. 9 to analyze the impact of the different strategies on each patient. Every time that a color red, green, or blue line takes negative values, a patient is in an unfavorable situation in relation to the original status. Consequently, having positive values means an improvement in total patient times. Some negative peaks can be observed in Fig. 9; all of them belong to the min–max and system efficiency strategy. Of the total number of patients with priority codes 3 (urgent), 6% are being affected negatively by strategy one and 9% by strategy two. For priority code one and two (semi-urgent and non-urgent), 10% are being affected negatively by strategy one and 16% by strategy two. Priority level 4 and 5 (emergent and immediate) are not affected. In models one and two, the total number of patients in unfavorable situations is equal to 7% and 8% of the total number of emergencies, respectively. In contrast, the game theory strategy never takes negative values in the impact axis, which means this strategy guarantees only positive changes to the patients.

6. Conclusion and future research directions

The allocation of emergency service requests to EDs has a significant effect on the whole system of healthcare delivery, from both financial and life-saving perspectives. To the best of our knowledge, this is the first study that incorporates MIP optimization models for the allocation of ambulances to reduce waiting times for treatment in EDs and thus decrease overcrowding in the US healthcare system. The incorporation of remote triage plays a fundamental role in this task. The patient priority codes combined with the utilization levels of EDs, provide the framework for centralized decision systems. Fully centralized allocation strategies by region can be used to improve the current policies. Nevertheless, the fact of existing disparities must be considered.

We have formulated three different strategies based on MIP, applying single-objective optimization, and bi-objective optimization. The first strategy is an efficiency-based model. The results presented in Table 6 show this model provided a significant improvement to the overall system. However, further analysis revealed the negative effect that the first strategy may have on some patients, despite the priority class assigned to them. The second strategy is a bi-objective model where we minimize the maximum time by priority class when patients travel more than 15 min. This consideration is added as a second objective function to the first strategy. This technique allows the decision-maker to control better the distribution of resources in circumstances of unfairness. As a result, there are multiple combinations of efficiency and fairness. Nevertheless, the min–max strategy has some disadvantages. Similar to the first strategy, some patients experienced a negative impact compared to the current conditions, particularly those traveling 15 min or less. Finally, our game theory strategy provides a solution that presents 26.42% system improvement. Additionally, it guarantees a positive effect for every patient with respect to the current conditions.

Given the results obtained, the present study provides a crucial quantitative advance in comparing centralized decision systems with decentralized ones. More importantly, the proposed strategies not only offer optimal assignment with fairness elements but can also be used as analysis tools for any EMS system. Under desired conditions, infeasible solutions can be interpreted as limitations of the system in terms of handling all emergency requests. The adjustment of parameters should result in insights about the changes required by the network, for example, changing the waiting time function parameter a_j of a given ED to estimated the lack of capacity.

Finally, based on the results presented in the previous section, the utilization of either strategy results in improved time to treatment, decreased waiting times, and less overcrowding. However, choosing the right one is vital to ensure the wellness of all patients. The results show that an efficiency-based model cannot be used by itself to improve

Table 6
Results summary.

Metrics	Decentralized	Efficiency	Min–max	Game theory
Average travel time (mins)	10.06	15.21	16	16.47
Average ED waiting time (mins)	36.41	16.67	16.48	17.72
Average total time (mins)	46.47	31.88	32.48	34.19
Total system improvement (mins, %)	–	1094 , 31.39	1049, 30.10	921, 26.42
Standard deviation	19.28	8.80	9.62	10.85

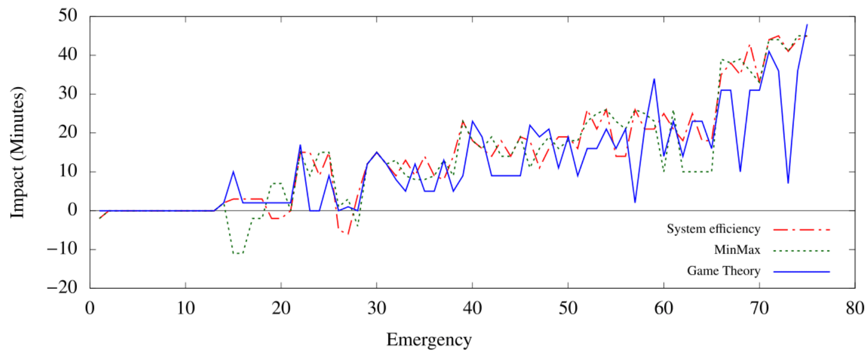

Fig. 9. Impact perceived by the patients in minutes.

systems in which patients at risk are involved. Efficiency strategies that incorporate fairness characteristics, as in the case of the min–max model, are potential solutions when scenarios similar to those described here are being studied. It is our opinion that the game theory strategy is the best way to guarantee the absence of negative impacts on all patients. Another positive aspect of strategies two and three is the flexibility offered by bi-objective models and non-symmetric bargaining games to adjust the results based on the system requirements.

In the future, we would like to generate a hybrid strategy where a new objective function is incorporated into the non-symmetric bargaining problem. This objective function could be related to rural areas, unattended illnesses, and other types of disparities. Besides, the development of new metrics to compare the strategies from an economic point of view can provide new insights to choose the best methodology. The models we propose and the results obtained disclose some understanding of the impact that allocation decisions in healthcare have on patients and the overall system. Future research that relaxes some of the assumptions and limitations of this study might prove useful. Uncertainties related to traffic or weather conditions may affect the final destination of an emergency. Also, the integration of a complete system view can help to disclose relationships between destination ED and dispatch policies for ambulances.

We consider implementation the next step, where the impact of strategies can be measured in a real-time data environment, providing insights on a daily basis and contrasted with the theoretical assumptions.

Appendix A. Model linearization

Linearization is a commonly used practice in the modeling of nonlinear functions. Linearization will come with the cost of introducing some new decision variables and constraints. First, let us consider a simplified case where both variables are binary. Suppose the model has the following product:

$$y \times z \tag{A.1}$$

where y and z are binary variables. Since $y \times z$ can take only 0 or 1 values, we can replace any instance of $y \times z$ in the model with a new binary variable x. We then add the following three constraints to the model to ensure that x will take proper values.

$$x \leq z \tag{A.2}$$

The previous inequality ensures that x will be equal to zero if z is zero.

$$x \leq y \tag{A.3}$$

Inequality (A.3) ensures that x will be equal to zero if y is zero.

$$x \geq z + y - 1 \tag{A.4}$$

The last inequality makes sure that if z and y are equal to one, then x is set to one. In this way, x will always represent the result of the product despite the values that y and z can take.

Now, let us consider a case where we try to linearize the product between a binary and a continuous variable, y and c respectively. Since $y \times c$ can take only 0 or c values, we can replace any instance of $y \times c$ in the model with a new continuous variable x. If c is bounded below by zero and above by a Big M (Large number), then we can add the following three constraints to ensure that x will take proper values.

$$x \leq M \times y \tag{A.5}$$

Inequality (A.5) ensures that if the binary variable is equal to zero, then the product of the continuous and binary variable has to be equal to zero. Conversely, if y is equal to one, the inequality will make x always smaller or equal than the upper bound of c.

$$x \leq c \tag{A.6}$$

The previous inequality considers that y is a binary variable; therefore, the value of the product can be at most equal to the value of the continuous variable c.

$$x \geq c - M(1 - y) \tag{A.7}$$

The inequality (A.7) will make sure that x is always greater or equal than c. Finally, considering the previous inequalities, we can be sure that x represents the product of y and c. Additional analysis can be done based on the structure of each model. For example, if the model

is trying to minimize the value of x, then inequalities (A.5) and (A.6) representing upper bounds are not needed. For more scenarios and similar cases we recommend to check the following Ref. [48].

Appendix B. Supplementary data

The data utilized in section four was randomly generated through processes that can be hard to replicate. Consequently, the data files and the instructions for their utilization are available at https://github.com/jorgeacunam.

Appendix C. Min–max strategy, additional solutions

Table 7 presents the results for each point in the non-dominated frontier of Fig. 4. The last column shows the number of patients receiving an adverse impact based on the chosen objective values.

Table 7
Min–max strategy results.

Objective values	Total time	Avg. time	SD	No. of negative impacts
6943.9, 4243.3	2436	32.48	9.62	6
6923.5, 4246.5	2425	32.33	9.57	6
6910.1, 4249.7	2416	32.21	9.52	5
6895.9, 4260.3	2423	32.31	9.25	7
6875.5, 4262.8	2409	32.12	9.23	6
6859.9, 4266.2	2407	32.09	9.11	7
6846.5, 4269.4	2405	32.07	8.99	5
6833.3, 4274.0	2395	31.93	8.95	5
6810.8, 4286.9	2393	31.91	8.82	5
6793.8, 4302.0	2391	31.88	8.80	5

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Appendix E: A Bilevel-Nash-in-Nash Model for Hospital Mergers in Health Care Markets: A Key to Affordable Care

A bilevel-Nash-in-Nash model for hospital mergers in health care markets: A key to affordable care

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Abstract

The increasing and exorbitant health care prices in the United States combined with a market concentration trend has more than 25 million people without basic health insurance per year. Increasing mortality rates, decreasing quality of life, preventable hospitalizations, and emergency department overcrowding are some of the consequences of the health care access crisis. This work introduces a bilevel-Nash-in-Nash approach to mimic health care market interactions among insurers, hospitals, and patients. We model eight different scenarios to account for hospital horizontal mergers, insurance network expansions, and SARS-CoV-2 effect over a set of market metrics, such as insurance premiums and quality of care. We use the proposed approach to analyze Hillsborough County in Florida, considering a demand of 1.2 million customers, 14 hospitals, 4 health insurances, and 15 diagnosed related groups. Results show that the quality of care does not increase with hospital mergers and that improving hospital competition can reduce by up to 13.7% the current insurance premiums. We also found that increasing the number of providers per insurance network reduces by up to 35% the premiums in concentrated hospital markets. Further analyses revealed that the changes in demand due to the SARS-CoV-2 pandemic should reduce insurance premiums (between 25% and 35%) and increase hospital reimbursement rates.

Keywords: Game theory, Operations research, Bilevel optimization, Health economics, Insurance premiums, Health care access

1 Introduction

Three decades ago, the constant increase in health care cost in the United States (US) was attributed to technological growth, recognized and accepted as the "march of science and the increased capabilities of medicine" [1]. However, the discourse has changed significantly. In the first decade of the twenty-first century, studies started to identify the high cost of care and the society's denial as the problem that still keeps millions of US citizens without basic health insurance [2, 3]. Nowadays, researchers and politicians identify competition as the cornerstone to balance and reduce costs in the US market-based health care system [4, 5]. Nevertheless, provider and health insurance markets becoming more concentrated has been a significant trend in the last decades [6, 7, 8]. In 2016, 72% of the US metros had hospital markets with Herfindahl–Hirschman Index (HHI), a commonly accepted measure of market

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concentration, with values classified as highly concentrated by the Department of Justice (DOJ) [9, 10]. Even though increased efficiencies could happen with provider consolidation, benefiting patients [4], studies have found that concentrated health systems are associated with higher hospital prices when mergers are present in the market. Furthermore, some cases showed an association between hospital mergers and higher mortality rates, showing that a price increase did not improve the quality of care [11, 12].

Although the high cost of care affects mainly low-income segments of the US society and exacerbates income inequality [13], in 2019, 66.5% of all bankruptcies in the US were tied to medical issues, and more than 26 million people did not have health insurance at any moment during the year [14, 15]. This translates into a health care access problem that carries several consequences, such as higher mortality rates, lower quality of life, late diagnosis, preventable hospitalizations, and emergency department overcrowding [16, 17, 18, 19].

In this work, we investigate the impact of hospital horizontal mergers on health insurance policy prices. We present a framework to mimic the dynamics of the market-based health care system in the US, where hospitals, insurers, and patients interact to determine the equilibrium prices among the hospital-insurers pairs. We test our model in a case study in Florida with different scenarios of competition and demand, including the impact of the SARS-CoV-2 pandemic. Our approach includes several system characteristics, such as the quality of care per institution, the patients' health condition, the cost of treatment per diagnosed related group (DRG), health insurance categories (metals), and demand household incomes.

1.1 Problem description

The US health care system is not only complex but is also one of the largest industries and a fundamental pillar of the US economy [20, 21]. This represents a challenge to any modification aiming to rebuild the system and highlights the need to improve the current structure.

Part of the complexity of the health system originates in the health insurance market. The insurance plans in the US are classified by metals based on how they split the costs with customers. For each category, the customer will pay a different percentage of the total annual cost of care. The most common categories are bronze, silver, gold, and platinum, where bronze has the lowest monthly premium and the worse coverage [22, 23]. Furthermore, each metal category may include different types of plans and networks. For example, an exclusive provider organization (EPO) is a type of plan where services are covered only if the patient uses providers (hospitals, doctors, specialists, etc.) that belong to the plan network. Preferred provider organization (PPO) is a type of plan where the patient pays less if the provider is in the plan's network; the patient can access outside network providers for an additional cost [24]. The three major mechanisms to get private health coverage are 1) a job group coverage plan, the 2) health insurance marketplace, and 3) purchasing the plan directly from an insurance company [25]. The advantage of the health insurance marketplace is that customers can qualify for lower premiums based on their income. In the case of a group health insurance plan, the employees and employer split the cost of care [26].

Hospitals are another source of complexity—the type of ownership, state/local government, for-profit, and non-profit defines the structures and behaviors of hospitals [27]. For-profit and non-profit hospitals represent more than 80% of the total hospitals in the US, and both generate profits. The difference lies in the tax status; the non-profit hospitals pay fewer taxes in exchange for contributing part of their revenues to the community. However, activities such as research and training/education in the same hospital are considered community benefits [28].

The health system has at least four significant characteristics affecting competitive interactions between entities [29]. First, insured patients primarily obtain hospital services through their insurance; hence the number of hospitals available to patients depends on the health insurance network.

Second, patients are relatively insensible to health prices; the insurances cover most inpatient care costs. Third, patients choose health insurance before a health shock. Therefore, hospitals can be considered an option demand market. Finally, hospitals and insurers define partnerships and negotiate the reimbursement rates hospitals get from treating insurer's enrollees.

In Figure 1, we present a general representation of the market system interactions. The sequence includes a system of negotiations between hospitals and insurers and a market where customers and patients maximize benefits. In the upper level of decisions, each hospital-insurer pair bargains to decide the reimbursement rates insurers will pay to hospitals. This determination will help to define the policy premiums insurers will offer to customers at the lower level. After that, each customer will choose insurance based on policy characteristics and the resources willing to spend. Finally, a health status draw will define if a customer remains healthy or need to select a hospital to get treatment.

The high cost of care in the US and the consequence of limited access to medical services are rec-

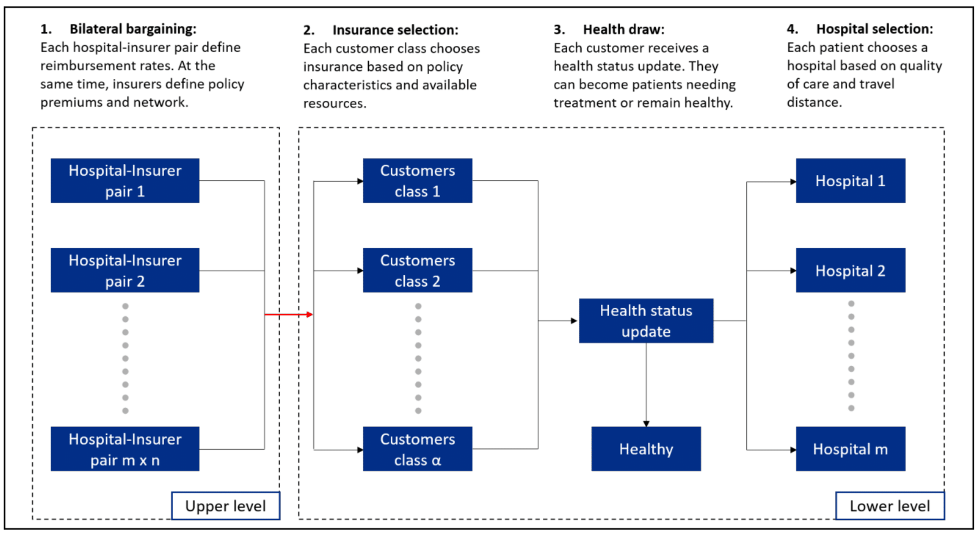

Figure 1: Health market system interactions

ognized internationally. According to the Organization for Economic Cooperation and Development (OECD), the US has the highest health expenditure by gross domestic product (GDP) and per person among all member countries [30]. Furthermore, the US has one of the lowest population coverage, only above Mexico and Costa Rica, and the worst public health coverage (among countries with public health) in the OECD [31]. Therefore, studies trying to understand the current market interactions and providing policy insights are imperative to design mechanisms for reducing health care costs.

1.2 Literature review

Several studies have been conducted in the health care market context. In this paper, we divided the literature into two central pillars of interest. The first considers publications implementing data analytics to understand the effects of changes in the health market structure over health prices and quality of care. Many studies have covered this pillar over the last two decades providing significant advances in identifying the consequences of lack of competition [32, 33, 34, 35, 36, 37, 38, 39]. We are interested in the second pillar, which focuses on modeling the health care market interactions to

gather insights and improve decision making. The following publications provide different modeling approaches to generate suggestions for policy design and management in health care markets.

The authors in [40] present a linear optimization framework based on revenue management to deal with the inefficiencies occurring after health network consolidations. The design informs strategic decisions for resource allocation and network building. Through a case study, the authors showed how to better use the spare surgical capacity in a health community network to capture lost demand and maximize profits. In [41], the authors used data envelopment analysis to evaluate the technical efficiency among hospitals and study the potential benefits from mergers. The results showed that sources of potential efficiency gains could be used individually, without the need for mergers. However, mergers could work as catalyzers to achieve the improvement. The authors in [42] implemented a bilevel game-theoretic model to estimate providers' willingness to join a health information exchange network. Under a set of assumptions, the study analyzed the influence of federal incentives/penalties over hospital collusions. The results suggested that information blocking of a subset of hospitals affected every hospital in the network and that financial incentives could not mitigate the adverse network effects. Using a model of employer-insurer and hospital insurer bargaining, the authors in [43] simulated the removal of small and large insurers to study the impact on premiums. The results showed that premiums typically increase but could fall after the removal of smaller insurers. In [44], the authors presented a bargaining model of competition between hospitals and managed care organizations (MCO) to analyze hospital mergers. The results showed that MCO bargaining helps restrain hospitals' prices and that increasing patient payments allows steering the demand towards cheaper hospitals. Furthermore, the authors concluded that standard oligopolies models do not accurately capture pricing fluctuations in these bargaining scenarios and that hospital mergers significantly raise prices. The authors in [45] studied the consequences of small hospital networks in health care markets. Through a Nash-in-Nash approach, they captured insurers' incentives to exclude hospitals. The results showed that private incentives to exclude often surpass social incentives, as the insurers benefit from a lack of negotiation on hospital rates. In [46], the authors study the motivation of vertical integration between physicians and hospitals as a mechanism to increase bargaining power with insurers. An extension of the known hospital-insurer bargaining model was presented by including endogenous hospital bargaining power (increase alignment with physicians). The results showed that physician-hospital alignment is associated with private insurers' market concentration.

The literature on modeling presented above can be divided into two main groups. The first group [40, 41, 42] uses optimization-based approaches to provide insights and applicable frameworks to improve health care markets. However, the efforts do not focus on the hospital-insurer-patient interactions and the influence on insurance premiums. The second group [43, 44, 45, 46] focuses on economic theory, where the optimal points (equilibrium) are mathematically derived. Therefore, several assumptions, such as convexity/concavity and constant marginal costs, might be needed (reducing applicability). Furthermore, the second group solves the patient stage combine with the bargaining stage as a single-level problem (with several phases). In reality, patients choose insurance after policy prices and reimbursement rates are defined, and patients, insurers, and hospitals know it. Having more information or letting other actors known one has more information can make a player worse-off. Therefore, changing the equilibrium in favor of the upper players [47].

1.3 Contributions

This paper proposes a framework to mimic health care market interactions among patients, hospitals, and insurers. Our objective is to study the impact of hospital horizontal mergers on insurance premiums, quality of care, and reimbursement rates through optimization-based methods. Furthermore, we examine the SARS-CoV-2 scenario and analyze the implications for insurance premiums and other system characteristics. Unlike previous approaches, we consider separate bilateral bilevel

problems (Stackelberg games) within a Nash equilibrium to a game played among customers (possible patients) and all pairs of hospital-insurer. We represent each hospital-insurer (leader) pair interaction through a Nash bargaining solution, and the demand/customers (follower) problem is solved using the Karush-Kuhn-Tucker conditions. We refer to this approach as the "bilevel-Nash-in-Nash" solution. The resulting mathematical model enables federal/state agencies to assess the potential benefits of policy implementation and to study the impact of structural changes in the market. We illustrate our work with a case study in Florida (US). However, the framework and methods can be contextually applied to other regions.

1.4 Structure

The article proceeds as follows. Section 2 introduces the model and the equilibrium concept. In Section 3, we present the case study in Florida, where the mathematical framework is applied. Section 4 presents the results and discussion. Finally, Section 5 shows the concluding remarks and future directions.

2 Mathematical model

This section presents the modeling approach to study the health market system interactions, where each player wants to maximize its benefit. The model combines game theory and optimization methods to account for the interaction among hospitals, insurers, and customers. Mathematically, the system can be formulated as a bilevel problem, see Figure 1, where the upper-level variables represent the utility functions of each hospital-insurer pair, and the lower-level is the utility function of patients' selection of insurance and hospital.

Let M and N be the set of hospitals and insurers bargaining in the region under analysis. In the presence of horizontal mergers, each hospital $i \in M$ will belong to a health system $e \in Z$. The exogenous demand is defined by d^{α} where $\alpha \in V$ represents a customer category, and $k \in L$ is the health condition of each patient. The upper-level formulation considers a Nash bargaining approach between each hospital $i \in M$ and insurer $j \in N$ to determine the reimbursement hospital i should get after treating a patient with insurance j. Therefore, maximizing the bilateral negotiation with each other in equilibrium. We assume that both hospital prices and insurance premiums are simultaneously determined. The Stackelberg (bilevel) structure implies that the upper-level requires input from the lower level, in this case, the demand for hospitals and insurances. Similarly, the lower-level requires the policy prices (premiums) to determine patients' insurance and hospitals. This dependency between upper and lower systems is understood as the relationship of a leader and follower in game theory, where the leader takes action first and the follower responds to this action.

In Table 1, the model indices, parameters, and variables are presented. Below we introduce the mathematical formulation of the upper-level problem.

2.1 Upper level formulation (bilevel A)

The upper-level formulation of each Stackelberg game is represented by a cooperative approach (Nash solution) between each hospital-insurer pair to maximize benefits. This approach assumes each pair defines a solution given all other pairs' agreement (full information). Let us consider u_j and h_i the utility functions of insurance j and hospital i. Objective (1) presents the maximization of benefits through cooperative bargaining, where u'_j and h'_i are the utility of hospital i and insurance j before the current negotiation. We consider i^* and j^* the pair under analysis.

$$\max\,(u_{j^*} - u'_{j^*})(h_{i^*} - h'_{i^*}) \tag{1}$$

Table 1: Model indices

Index	Definition
i	Hospital i, where $i \in M$
e	Hospital health system e, where $e \in Z$
j	Health insurance j, where $j \in N$
k	Diagnosis k, where $k \in L$
α	Customer class α, where $\alpha \in V$
Parameter	**Definition**
w_k	Weight applied to reimbursement rates based on diagnosis k
c_i^k	Cost of treating a patient with diagnosis k in hospital i
π_j	Administrative cost of insurance j
η_j	Net income rate of insurance j
ω_i	Quality of care of hospital i
ϵ_i^α	Distance between hospital i and customers of class α
β_i^α	Weight assigned by customers of class α to the quality of care of hospital i
d^α	Insurance demand per customers of class α
$Pr(k)$	Probability of needing treatment with diagnosis k
σ_1^α	Weight assigned by class α to the network of each insurance
σ_2^α	Weight assigned by customers of class α to the premium of each insurance
z_{ij}	Binary parameter equal to 1 if hospital i and insurance j agree to have a contract, 0 otherwise
s_{ij}^α	Score assigned by customers of class α with insurance j to hospital i based on the quality of care and location
f_α	Maximum acceptable policy price by customers of class α
Variable	**Definition**
u_j	Utility function of insurance j
h_i	Utility function of hospital i
g_e	Utility function of hospital health system e
p_i^j	Base price to be paid by the insurance j to hospital i when treating an enrollee
t_e^j	Base price to be paid by the insurance j to hospital health system e when treating an enrollee
$q_{ij}^{k\alpha}$	Number of patients of class α with insurance j to be served in hospital i due to diagnosis k
r_j^α	Total revenue of insurance j obtained from customers of class α
δ_j^α	Proportion of customers of class α selecting insurance j
x_j^α	Score assigned to insurance j by customers of class α

Constraint (2) presents the total revenue of insurance j^* obtained from customers of class α. This value is calculated considering the total expenditure related to class alpha multiplied by one plus the desired net income rate. In this equation, $p_i^{j^*}$ is the base price (reimbursement rate) to be paid to

hospital i by insurance j^* when treating an enrollee. This base price is multiplied by the diagnose weight w_k of each patient. $q_{ij^*}^{k\alpha}$ represents the number of patients of class α with plan j^* to be served at hospital i due to diagnose k. η_{j^*} is the desired net income rate and π_{j^*} is an administrative cost of insurance j^*.

$$r_{j^*}^{\alpha} = \left[\left(\sum_{i\in M}\sum_{k\in L} p_i^{j^*} w_k q_{ij^*}^{k\alpha}\right) + \pi_{j^*}\right](1+\eta_{j^*}) \quad \forall\, \alpha \in V \tag{2}$$

In equation (3), the total revenue of insurance j^* obtained from customers of class α before the current bargaining with hospital i^* is calculated. Similarly to constraint (2), ${p'}_i^{j^*}$ and ${q'}_{ij^*}^{k\alpha}$ represent the base price and number of patients, but in this case, before negotiations.

$${r'}_{j^*}^{\alpha} = \left[\left(\sum_{i\in M}\sum_{k\in L} {p'}_i^{j^*} w_k {q'}_{ij^*}^{k\alpha}\right) + \pi_{j^*}\right](1+\eta_{j^*}) \quad \forall\, \alpha \in V \tag{3}$$

The equality constraints (4) and (5) present the utility functions of insurance j^* after and before the current negotiation. Each function is calculated as total revenue minus payments to hospitals and administrative costs.

$$u_{j^*} = \sum_{\alpha\in V} r_{j^*}^{\alpha} - \sum_{i\in M}\sum_{k\in L}\sum_{\alpha\in V} p_i^{j^*} w_k q_{ij^*}^{k\alpha} - \pi_{j^*} \tag{4}$$

$${u'}_{j^*} = \sum_{\alpha\in V} {r'}_{j^*}^{\alpha} - \sum_{i\in M}\sum_{k\in L}\sum_{\alpha\in V} {p'}_i^{j^*} w_k {q'}_{ij^*}^{k\alpha} - \pi_{j^*} \tag{5}$$

Equation (6) presents the utility function of hospital i^*. The value is calculated as the total payments received from the insurers minus the total cost incurred in treating patients. The marginal cost of treating a patient with diagnosis k in hospital i^* is given by $c_{i^*}^k$. Similarly, equation (7) calculates the utility function of i^* before the current negotiation.

$$h_{i^*} = \sum_{j\in N}\sum_{k\in L}\sum_{\alpha\in V} (p_{i^*}^j w_k - c_{i^*}^k) q_{i^*j}^{k\alpha} \tag{6}$$

$${h'}_{i^*} = \sum_{j\in N}\sum_{k\in L}\sum_{\alpha\in V} ({p'}_{i^*}^j w_k - c_{i^*}^k) {q'}_{i^*j}^{k\alpha} \tag{7}$$

In constraint (8), the score assigned by customers of class α with insurance j to each hospital i is estimated. The value considers the quality of care ω_i and the distance to the hospital ϵ_i^{α}. The binary parameter z_{ij} is equal to 1 if the hospital i and insurer j have an agreement (i is in j network), 0 otherwise.

$$s_{ij}^{\alpha} = z_{ij}(\beta_i^{\alpha}\omega_i + \epsilon_i^{\alpha}) \quad \forall\, i \in M,\, j \in N,\, \alpha \in V \tag{8}$$

In (9), the value of the base price for hospital i and insurer j is initialized for all pairs different than (i^*, j^*). Constraint (10) also assigns the value of the reimbursement rate ${p'}_i^j$ to all pairs before the current negotiation. Therefore, only $p_{i^*}^{j^*}$ remains unknown.

$$p_i^j = price_i^j \quad \forall\, [i \neq i^*\, and\, j \neq j^*] \tag{9}$$

$${p'}_i^j = price_i^j \quad \forall\, i \in M,\, j \in N, \tag{10}$$

Constraint (11) and (12) establish the axiom of individual rationality; no player in the current pair will accept a payoff (utility) lower than the disagreement point (utility before current negotiation).

$$u_{j^*} - {u'}_{j^*} \geq 0 \tag{11}$$

$$h_{i^*} - {h'}_{i^*} \geq 0 \tag{12}$$

Constraints (13) and (14) define the range and type of variables used in the upper level.

$$u_{j^*},\, h_{i^*},\, p_{i^*}^{j^*} \in \mathbb{R}^+ \tag{13}$$

$$r_{j^*}^{\alpha} \in \mathbb{R}^+ \quad \forall\, \alpha \in V \tag{14}$$

We next introduce a modified version of the upper level in which horizontal mergers among hospitals are allowed.

2.2 Mergers upper level (bilevel B)

Hospital horizontal mergers change the market structure affecting the health care access received by patients. In this modified upper-level, we assign each hospital to a health system, where the health systems can have one or more providers in their network. The formulation considers the bargaining between the insurer j^* and the health system e^*. Objective (15) shows the negotiation of each pair, where g_{e^*} and ${g'}_{e^*}$ represent the utility functions of health system e^* after and before the current bargaining.

$$\max\, (u_{j^*} - {u'}_{j^*})(g_{e^*} - {g'}_{e^*}) \tag{15}$$

subject to (2)–(5), (8), (11), (13), (14), and

Constraints (16) and (17) show the utility functions of hospital i. In contrast with equations (6) and (7), the modified upper-level requires the utility of every hospital i in health system e^*.

$$h_i = \sum_{j \in N} \sum_{k \in L} \sum_{\alpha \in V} (p_i^j w_k - c_i^k) q_{ij}^{k\alpha} \quad \forall\, i \in e^* \tag{16}$$

$$h'_i = \sum_{j \in N} \sum_{k \in L} \sum_{\alpha \in V} ({p'}_i^j w_k - c_i^k) {q'}_{ij}^{k\alpha} \quad \forall\, i \in e^* \tag{17}$$

Given that a set of hospitals generates a health system, the utility functions of the health system e^* are calculated in equations (18) and (19) as the sum of hospitals utility belonging to e^*, after and before the current negotiation respectively.

$$g_{e^*} = \sum_{i \in e^*} h_i \tag{18}$$

$${g'}_{e^*} = \sum_{i \in e^*} {h'}_i \tag{19}$$

Constraint (20) establishes the axiom of individual rationality of health system e^*; it will not accept a payoff (utility) lower than the disagreement point (utility before current negotiation).

$$g_{e^*} - {g'}_{e^*} \geq 0 \tag{20}$$

In equation (21) the reimbursement rate of insurance j to provider i (p_i^j) is defined to be equal for every hospital i that belongs to health system e.

$$p_i^j = t_e^j \quad \forall\, e \in Z,\, j \in N,\, i \in e \tag{21}$$

In (22), the value of the base price for health system e and insurance j is set for all pairs different than (e^*, j^*). Constraint (23) also assigns the value of the reimbursement rate ${p'}_i^j$ to all pairs before the

current negotiation. Therefore, only $t^{j^*}_{e^*}$ remains unknown. Constraint (24) defines the range of the variables g_{e^*} and $t^{j^*}_{e^*}$.

$$t^j_e = price^j_e \quad \forall\, [e \neq e^*\, and\, j \neq j^*] \tag{22}$$

$$p'^j_i = price^j_e \quad \forall\, e \in Z,\, j \in N,\, i \in e \tag{23}$$

$$g_{e^*},\, t^{j^*}_{e^*} \in \mathbb{R}^+ \tag{24}$$

We next introduce the lower-level of the Stackelberg game. This formulation is used for both the upper-level and the modified upper-level with horizontal mergers.

2.3 Lower level (Market Demand)

The lower-level optimization problem maximizes the utility of patients after the policy premiums have been decided. Therefore, it requires input from the upper level to generate an assignment process. This embedded problem generates the number of patients ($q^{k\alpha}_{ij}$) of class α with diagnosis k and insurance j to be treated in hospital i. In objective (25) the variable δ^α_j represent the proportion of customers of class α selecting insurance j, while x^α_j is the score given to insurance j by customers α. Therefore, the goal of (25) is to select the δ^α_j, for all j and α, that maximizes the total utility of demands d^α.

$$\max \sum_{j\in N} \sum_{\alpha \in V} \delta^\alpha_j d^\alpha x^\alpha_j \tag{25}$$

Constraint (26) calculates the score assigned by customers of class α to insurance j. This equation has two components. The first considers the insurance network through the sum of hospitals' score s^α_{ij}, and the second the difference between the maximum acceptable policy price f_α for customers of class α and the actual insurance premium. Each component is weighted depending on the class α using σ^α_1 for network and σ^α_2 for premium.

$$x^\alpha_j = \sigma^\alpha_1 \sum_{i\in M} s^\alpha_{ij} + \sigma^\alpha_2 \left(f_\alpha - \frac{r^\alpha_j}{\delta^\alpha_j d^\alpha} \right) \quad \forall\, j \in N,\, \alpha \in V \tag{26}$$

In (27) the number of patients class α with insurance j to be treated at hospital i due to diagnosis k is determined. The equation considers the proportion of customers class α with insurance j multiplied by demand d^α and the probability of getting sick with diagnosis k. The assignment to hospital i is based on the score s^α_{ij}. Similarly, constraint (28) calculates the number of patients before the current negotiation.

$$q^{k\alpha}_{ij} = \delta^\alpha_j d^\alpha Pr(k) \frac{s^\alpha_{ij}}{\sum_{i\in M} s^\alpha_{ij}} \quad \forall\, i \in M,\, j \in N, k \in L,\, \alpha \in V \tag{27}$$

$$q'^{k\alpha}_{ij} = \delta'^\alpha_j d^\alpha Pr(k) \frac{s^\alpha_{ij}}{\sum_{i\in M} s^\alpha_{ij}} \quad \forall\, i \in M,\, j \in N, k \in L,\, \alpha \in V \tag{28}$$

Constraint (29) defines the maximum premium a customers of class α can accept.

$$r^\alpha_j \leq f_\alpha \delta^\alpha_j d^\alpha \qquad \forall\, j \in N,\, \alpha \in V \tag{29}$$

In (30), the proportion of customers of class α with insurance j before the current negotiation is set.

$$\delta'^\alpha_j = prior^\alpha_j \qquad \forall\, j \in N,\, \alpha \in V \tag{30}$$

Constraint (31) limits the sum of insurance demand proportions for customers class α to be smaller or equal to one. Finally, in (32), the lower-level variables are defined.

$$\sum_{j\in N} \delta^\alpha_j \leq 1 \qquad \forall\, \alpha \in V \tag{31}$$

$$x^\alpha_j,\, q^{k\alpha}_{ij},\, \delta^\alpha_j \in \mathbb{R}^+ \quad \forall\, i \in M,\, j \in N,\, k \in L,\, \alpha \in V \tag{32}$$

2.4 Model solution: A bilevel-Nash-in-Nash approach

We now introduce the bilevel-Nash-in-Nash solution that characterizes the model equilibrium and necessary techniques.

Bilevel optimization models have been widely studied in the literature [48, 49, 50]. This optimization approach includes two mathematical programs, where one of these problems is part of the constraints of the other. In our case, given a lower-level program with a non-empty feasible set and convex objective function, the Karush-Kuhn-Tucker (KKT) equations provide the necessary conditions for a solution to be optimal (subject to constraint qualifications). Therefore, replacing the lower-level problem with the KKT conditions (see Appendix A) into the upper-level yields a mathematical problem with equilibrium constraints (MPEC). Interested readers can find additional information regarding the MPEC in [51, 52, 53].

The representation of each bilevel (Stackelberg) problem between a hospital-insurer pair and the customers as an MPEC generates an equilibrium program with equilibrium constraint (EPEC), defined as $EPEC = [(MPEC)_1^{mxn}]$. In general, MPECs have non-convex feasible sets due to complementary slackness. In addition, the upper-level problem presents a non-linear objective function, making challenging the task of finding the EPEC solution. However, recent developments in Gurobi 9.0 allow users to solve non-convex quadratic problems to global optimum [54].

The equilibrium find it in the EPEC problem is the vector of prices and demand decisions with $n(m+v)$ elements

$$\left((p_i^j*)_{[i=1,\ldots,m],[j=1,\ldots,n]}, (\delta_j^\alpha*)_{[j=1,\ldots,n],[\alpha=1,\ldots,v]}\right)$$

such that $\left((p_i^j*)_{[i=1,\ldots,m],[j=1,\ldots,n]}\right)$ maximizes the utility of each hospital i and insurer j in the upper-level problem and $\left((\delta_j^\alpha*)_{[j=1,\ldots,n],[\alpha=1,\ldots,v]}\right)$ maximizes the benefit of every group of customers class α in the lower-level program.

Several approaches to solve EPECs are available in the literature, where the most frequent are diagonalization methods [55, 56] and non-linear complementarity formulations [57]. In this study, we consider a diagonalization method algorithm as presented in [58] to solve the EPEC.

To deal with the negotiation problem between hospitals and insurers, we implement the Nash bargaining solution (NBS) in each upper-level problem. The NBS is a cooperative approach that yields a unique Pareto solution in the bargaining problem where players need to share a payoff they jointly generate. Pareto optimality implies a trade-off in the solution among players. Furthermore, the NBS guarantees individual rationality; no player will accept a payoff lower than the disagreement point (utility before negotiations). Additional information regarding the NBS and its applicability can be found in [59, 60, 61].

3 Case study

This section presents a case study based on Hillsborough County (Florida) in the US. Hillsborough is the largest county in the Tampa Bay area covering 1,266 square miles with a population of 1.4 million. In 2017, Tampa Bay was classified with an HHI of 2,446 and a price 6% above the country's median [62]. According to the DOJ, an HHI between 1,500 and 2,500 is considered moderately concentrated, and any value over it is highly concentrated. This case study uses the 2017 Healthcare Cost and Utilization Project (HCUP) databases, where we combined the State Inpatient Databases (SID) [63] with the Cost-to-Charge Ratio (CCR) files [64]. The SID covers 97% of all discharges in community hospitals across the US, while CCR is supplementary data linked to SID to estimate inpatient care costs.

According to the Florida Agency for Health Care Administration, Hillsborough County has 16

hospitals, of which 14 are short-term acute care facilities [65]. We identified these 14 institutions in the Florida SID database 2017 to collect most of the information needed by our model. In 2019, according to the US Census Bureau, 86% of the population in Florida had health insurance [66]. Therefore, our case study considers a demand of 1.2 million customers in Hillsborough County seeking insurance. Considering the information provided by [63, 66], we estimated that 14% of the 1.2 million would require care at some point of the year. For simplicity, we considered the 15 most frequent DRGs in the data as possible diagnoses (k). Using a binomial distribution and the patient data in SID 2017, we determined customers' probability ($Pr(k)$) of getting diagnosed with one of the 15 DRG.

To assess the quality of care (ω_i), we considered the HCAHPS survey requested to all hospitals in the US by the Centers for Medicare and Medicaid Services (CMS) [67]. This survey is publicly available and gives a view on patient's perception, impacting the institutions' reputation with values ranging between one (worst) and five (best) [68]. SID 2017 provides the median household income (four quartiles) for the patient's zip code. We used these ranges to classify the demand into four different classes (α) and the zip codes to estimate the distance (ϵ_i^α) between each hospital and class (values between one (worst) and five (best) to match the quality score). We assumed that all classes give the same importance to quality and travel distance ($\beta_i^\alpha = 1$). However, given the income difference, we considered several values (0.25, 0.5, 0.75, and 1) for σ_1^α (network) and σ_2^α (premium). For example, the class with the lowest income have $\sigma_1^1 = 0.25$ and $\sigma_2^1 = 1$, while the wealthiest class have $\sigma_1^4 = 1$ and $\sigma_2^4 = 0.25$ (in equation (26) the values multiplying σ_1^α and σ_2^α were normalized to match in scale).

Combining the hospital-specific all-payer inpatient cost/charge ratio (CCR file) with the median price per DRG in each hospital, we estimated the treatment cost per DRG and hospital (c_i^k). The diagnosis weights (w_k) applied to base prices (p_i^j) were obtained from the Medicare severity diagnosis related groups (MS-DRGs) [69]. CMS annually updates the payment weights of MS-DRGs to make sure each group contemplates cases requiring a comparable amount of resources. We assigned a maximum premium price (f_α) for each class of customers based on the average maximum premium (among adults younger than 60 years old) per insurance metal category (bronze, silver, gold, and platinum) in the Health Insurance Marketplace of Hillsborough County [70].

Finally, we set four insurances to negotiate with the 14 hospitals. Each insurance network (z_{ij}) was defined based on the four insurer companies in Hillsborough County providing EPO plans [70]. Considering the total annual revenues and net income of the four largest insurers in Florida (based on revenues as of December 31, 2019) [71], we estimated the desired net income rates (η_j). For simplicity, we set the insurance administrative costs to zero ($\pi_j = 0$).

4 Results and discussion

In this section, we present and discuss the results of implementing our mathematical model in Hillsborough County. We considered seven additional scenarios to contrast with the baseline (case study) of existing mergers. First, we design a competitive system where hospitals act separately when negotiating with insurers; we used the bilevel A approach to consider this case. Then, we extend the baseline and competitive analysis to scenarios where all hospitals are included in each insurance network. Finally, we examined the impact of a modified patient demand due to SARS-CoV-2 for the four previous scenarios. In Table 2, we summarize the eight different scenarios' characteristics.

The mixed-integer programming (MIP) problems representing each scenario were implemented in JULIA 1.5.1 and solve using Gurobi 9.0.3. Employing the bilevel B approach and the case study, we obtained the baseline scenario results. According to our model, the average monthly insurance premium in Hillsborough county costs $646, while the real average premium among metals in Florida for 2021 was $612 [72]. However, CMS projected a yearly increase in health insurance spending of 5.1% between 2020 and 2027 [73]. Therefore, we considered the 5% variation of our model acceptable

Table 2: Description of model scenarios.

Scenarios	Regular demand	SARS-CoV-2 demand	Insurances real networks	Insurances perfect networks	Hospital mergers allowed	Independent hospitals
Baseline	✓		✓		✓	
Competitive	✓		✓			✓
Enhanced-baseline	✓			✓	✓	
Enhanced-competitive	✓			✓		✓
Covid-baseline		✓	✓		✓	
Covid-competitive		✓	✓			✓
ENH-Covid-baseline		✓		✓	✓	
ENH-Covid-competitive		✓		✓		✓

Abbreviations: Covid, SARS-CoV-2; ENH, Enhanced

Table 3: Summary of model results per scenario under regular demand.

Scenarios	Insurance premium weighted average†	Quality of care weighted average‡	Equilibrium* average price	Hospitals** total net income	Insurances*** total net income
Baseline	646	3.29	44718	8106.07	201.21
Competitive	558	3.24	42734	7034.40	169.32
Enhanced-baseline	417	3.56	36385	5030.52	117.58
Enhanced-competitive	456	3.56	37380	5597.69	128.92

† Values in US dollars per month.

‡ Values in a scale between 1 (worst) and five (best).

* Values in US dollars per patient, ** Values in million of dollars.

in the current context and small enough to validate our results. The summary of the model results per scenario is shown in tables 3 and 4. These tables include the weighted average health insurance premium and quality of care, the average equilibrium price, and hospitals and insurances' total net incomes.

4.1 Regular market demand conditions

The first group of scenarios considers the regular demand for health services in Hillsborough County, as presented in the case study. When comparing the baseline and competitive scenarios (Table 3), it is noticed that hospital mergers (baseline) produced average insurance premiums of $646, while independent hospitals (competitive) generate average premiums of $558 in the system. Therefore, a 13.7% of reduction could be achieved by increasing hospital competition and avoiding horizontal mergers. This result aligns with findings in the literature suggesting that hospital mergers increase health care prices [11, 12]. In terms of quality of care, the baseline and competitive scenarios have similar scores, 3.29 and 3.24, respectively. Furthermore, equilibrium prices and hospitals and insurances net incomes follow the same tendency as premiums, being higher at the baseline scenario.

A promising finding arises when analyzing the enhanced baseline and enhanced competitive strategies (Table 3). These two scenarios assume that all hospitals participate in the network of each insurance. Therefore, the quality of care received by patients is the same, 3.56. Both approaches show average premiums less expensive than the competitive scenario ($558). However, in this instance, the Enhanced-baseline generates a smaller average premium compared to the Enhanced-competitive, $417 and $456, respectively. This behavior contradicts what was found in the first two scenarios and brings an interesting question. Can systems allowing hospital mergers to offer lower prices than very compet-

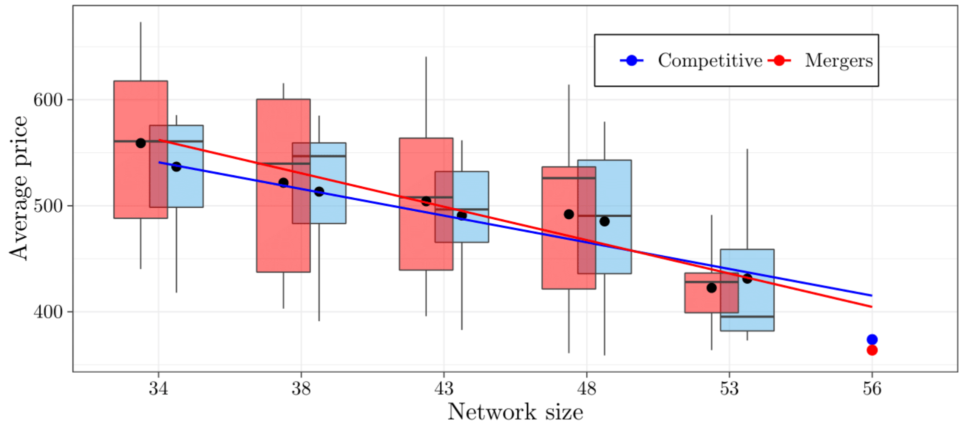

Figure 2: Effect of insurance network size on average equilibrium price in competitive and non-competitive markets

itive hospital markets? To ensure that our finding is not just specific to the utopian network scenario, we run 100 additional cases, adding randomly and gradually more hospitals to each insurance network.

In Figure 2, we present the progression from the actual network size to the utopian/full network (56 agreements). We fitted a linear regression to each market structure, blue for competitive and red for mergers. As noticed, as the number of hospitals in the insurers' networks increases (x-axis), both scenarios reduce their equilibrium prices (y-axis). Nonetheless, the lines intersect around the 48 agreements; from that point, the bargainings considering the hospital health systems (mergers) provide lower prices than bargainings with individual hospitals. Furthermore, the boxplots' interquartile range and whiskers for mergers are reduced with the network size increase. This implies less price dispersion among the random scenarios.

The results presented in Figure 2 can be understood if we considered the following intuitive explanations. First, the minimum base price (reimbursement rate) an individual hospital can accept is determined by its cost; in other words, as long as the hospital has a positive utility, the base price is feasible. Second, given that every hospital in the model has different costs (efficiencies), they will also have different price thresholds to keep a positive financial balance. Third, in the case of hospital mergers (health systems), the utility functions of individual hospitals are aggregated. Consequently, a merger has a broader price threshold for keeping a positive balance, i.e., some hospitals in a merger could have zero or slightly positive utility, and the merger still could make significant profits with the more efficient hospitals for the given reimbursement rate. However, due to the decrease in competition when mergers are allowed, hospital health systems are not forced to use the lower part of their feasible price ranges. Finally, as insurances commence to include more hospitals in their networks, more price negotiation occurs, and additional alternatives appear. This translates into an increase in bargaining power that insurers can use to move down in the feasible price ranges of mergers.

4.2 SARS-CoV-2 market demand conditions

We now present the results obtained when implementing our model in Hillborough county with modified demand due to SARS-CoV-2. Although one might anticipate health costs to increase during the pandemic, recent articles have found that spending and utilization have gone down [74, 75]. According

Table 4: Summary of model results per scenario under SARS-CoV-2 demand.

Scenarios	Insurance premium weighted average†	Quality of care weighted average‡	Equilibrium* average price	Hospitals** total net income	Insurances*** total net income
Covid-baseline	444	3.23	45862	6420.47	149.91
Covid-competitive	414	3.23	43794	5136.98	117.51
ENH-Covid-baseline	300	3.56	36362	3630.27	84.82
ENH-Covid-competitive	328	3.56	37271	4021.19	92.64

Abbreviations: Covid, SARS-CoV-2; ENH, Enhanced.

† Values in US dollars per month.

‡ Values in a scale between 1 (worst) and five (best).

* Values in US dollars per patient, ** Values in million of dollars.

to a study using Massachusetts (US) data, the change in overall hospital admissions of patients with private insurances was -28% between 3/11/2020 and 9/8/2020 [76]. Therefore, we used this estimation to modify the percentage of customers requiring health services in our system from 14% to 10%.

In Table 4, the results of applying the modified demand in four different scenarios are presented. Similar to the results obtained in the regular demand scenario (Table 3), the Covid-baseline shows a higher average premium than the Covid-competitive, $444 and $414, respectively. This implies that even in unfavorable demand scenarios, increasing hospital competition and avoiding horizontal mergers can reduce the average premium, in this case by 7%. In addition, the quality of care of Covid-baseline and Covid-competitive are the same (3.23). This reaffirms the results seen in Table 3 showing almost zero improvements in quality of care through mergers.

The enhanced insurance network scenarios for Covid-baseline and Covid-competitive show the same pattern found in the regular demand enhanced scenarios, where mergers generate lower average premiums than competitive hospitals, in this case, $300 vs. $328.

An interesting observation is the relationships between the equilibrium prices and net incomes shown in tables 3 and 4. As can be observed, the equilibrium prices (reimbursement rates) in the SARS-CoV-2 scenarios are similar or higher than those presented in Table 3, but the net incomes are lower. This relates to the decrease of patients demand and how the insurances and hospitals share the payoffs they jointly generate. Regardless of the increase in average equilibrium prices with SARS-CoV-2, the premiums get between 25% and 31% less expensive than in the regular demand scenarios. Unfortunately, despite the promising results obtained with our model showing a reduction of premiums during SARS-CoV-2 and recent studies indicating a decrease in health spending [74, 75], most insurers kept or increased the premiums for 2021, claiming uncertainty surrounding demand for delayed health services in 2020 [75]. Moreover, at the end of the third quarter of 2020, the average gross margins among private insurers were 21% higher than at the same point in 2019 [77]. Conversely, hospitals face decreasing margins, and it is expected that during 2021 the hospital revenue would likely be down between $53 and $122 billion [78]. Therefore, health insurance companies are not transferring the savings in health expenditure to the patients and neither sharing the payoffs with hospitals.

5 Concluding remarks and future directions

The internationally recognized health care access problem in the US [30, 31], associated with high costs of medical services, keeps millions of citizens without basic health insurance [2, 3]. Higher mortality rates, lower quality of life, preventable hospitalizations, and emergency department overcrowding are some of the consequences of the lack of health care access in the US [16, 17, 18, 19]. To our knowledge, this is the first study that presents a mathematical framework anchored in bilevel optimization and

game theory to mimic interactions among insurers, hospitals, and patients to set insurance premiums. We analyzed the impact on reimbursement rates and quality of care (among others) of hospital horizontal mergers, insurance network enhancements, and demand fluctuations due to SARS-CoV-2. We developed a "bilevel-Nash-in-Nash" approach to design and solve our models. This approach considers separate bilateral bilevel problems (MPECs) within a Nash equilibrium to a game played among customers and all pairs of insurer-hospital (EPEC). We solve each pair interaction (upper-level) through a Nash bargaining solution, and we use the Karush-Kuhn-Tucker conditions to deal with the lower-level problem (customers). In the scenarios where hospital horizontal mergers are allowed, we replace the insurer-hospital pairs with insurer-health system pairs. To find the Nash equilibrium to the EPEC, we implement a diagonalization method using Gurobi 9.0.3.

The proposed model is used to analyze the Hillsborough County (Florida) health care market and the impact of existing hospital mergers on the health insurance premiums. Results show that hospital market concentration increases health care prices and does not improve the quality of care. Furthermore, a 13.7% reduction on average premiums could be achieved by increasing hospital competition and reducing mergers ($646 vs. $558). We also found that increasing the number of providers in the insurance networks benefits patients in competitive and oligopolistic markets. Surprisingly, for large enough insurance networks, lower policy premiums can be obtained in concentrated hospital markets. Therefore, expanding insurance networks is an excellent mechanism for dealing with markets where mergers have already been placed. The results show a possible premium reduction of up to 35% in premiums for the concentrated market ($646 to $417) and up to 18.3% for the competitive market ($558 to $456).

We run four additional scenarios to understand the impact of the SARS-CoV-2 in the health market. Results show that the decrease in admissions associated with the pandemic should reduce average insurance premiums. In the case of concentrated hospital markets, premiums should change from $646 to $ 444 (31% reduction), and in competitive markets from $558 to $414 (25%). Furthermore, equilibrium prices (reimbursements rates) should rise to avoid hospitals' margin depression. These findings contradict the current status of the health market where insurers have kept or increase their premiums, and hospitals are facing financial challenges [78, 75].

In summary, we presented a practical bilevel-Nash-in-Nash approach to mimic health care market interactions and analyze key metrics such as insurance premiums and quality of care. The findings indicate that 1) quality of care does not increase with hospital mergers and that 2) avoiding them (or improving hospital competition) is critical to prevent increments in health prices. Furthermore, 3) expanding insurance networks is an excellent mechanism to reduce policy premiums in already concentrated hospital markets. Finally, 4) the reduction in hospital admissions due to SARS-CoV-2 should translate into savings for patients when purchasing health insurance. Policymakers can use the proposed model to determine the impact of future mergers and design incentives/penalties structures that will promote competition for the benefit of patients. Future research exploring different negotiation mechanisms in hospital mergers and considering bargaining among insurance for premium determination might prove helpful.

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