Health or Wealth: An Analysis of Healthcare Negotiations

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Abstract

This study examines the negotiations of healthcare prices between hospitals and insurance companies for patients in need of a C-section. To conduct the study, we simulate an ultimatum game by generating synthetic data based upon specific assumptions. We utilize the evolutionary game theory concept of Nash Equilibrium when examining the negotiations between hospitals and insurance companies. We simulate negotiations and transactions for each patient who requires services. This continues until either the hospitals' capacity reaches the limit, or the maximum number of rounds is reached. The resulting data reveals insights regarding the count of accept and reject decisions, patient welfare, and patient wait time. Our analysis provides information regarding the deficiencies and inequities within the healthcare system, which result in inadequate outcomes for patients.

1 Introduction

In late 2022, American healthcare costs reached an all-time high [1]. These mounting costs prevented ailing citizens from receiving necessary services, further sparking debate on healthcare affordability. Across these discussions, a general question underpins the dialogue surrounding the Affordable Care Act and broader health reform: how can the government facilitate the most equitable and affordable healthcare for its citizens? With that notion in mind, as a part of hospital price transparency, on July 1, 2022, government regulators legally mandated health insurance providers to publish their price negotiations with health providers. This federally released data—in theory—allows patients to compare insurance companies against one another to promote fairness and maximize their spending power. However, consumers struggle to access these statistics due to the file size and lack of standardized formats. This continued obscurity emanates from the intricacies of the bargaining interactions between insurance and health providers.

Following these negotiations, according to *The New York Times* [2] data, major health insurers frequently present unfavorable rates to their customers—occasionally leaving the consumer better off pretending not to have the coverage to receive the lower uninsured discount rate. As insurance companies contract rates on behalf of a client base, they exert greater market power than individual consumers with the intent of offering lower rates. Notably, in smaller markets with either few insurers or a predominant hospital, health providers often hold greater market power; however, as markets approach perfect competition with a more diversified health system, insurance providers hold greater bargaining power [3]. Despite their mission to attend to patients, per *The Washington Post* [4] and Oliver Wyman [5], healthcare providers with considerable market power negotiate higher prices and continue to demand post-covid price hikes extending into 2023 negotiations, placing further costs on consumers. Yet, given the ambiguity of these negotiations, patients remain uninformed of the nature of their medical care pricing.

The inefficiency of the healthcare and health insurance bargaining process takes a significant toll on consumers. Notably, the average cost of a cesarean birth remains $3,214 with insurance [6]. As a common, life-saving procedure, C-sections serve as valuable examples through which to examine this negotiation process, particularly through the lens of evolutionary game theory. Studying the behavior of large populations engaging in strategic interactions, evolutionary game theory—despite its biological origins—helps contextualize and model decision-making in social systems through processes such as the ultimatum game [7], [8]. This economic exchange examines agents' valuation of fairness and reciprocity. Placing a proposer and responder with associated monetary interests into a 'take it, or leave it' scenario, the ultimatum game dynamics mirror the price negotiations of healthcare and health insurance providers.

Improving public understanding of healthcare negotiations holds major power in modern politics. With an increasingly partisan political atmosphere, the dissemination of this bargaining information maximizes patient spending power and lessens patient dependency on unlikely bipartisan reformative policies in a party-adherent era. Thus, spotlighting and clarifying health provider and health insurer negotiations empowers the consumer to seek change and spend efficiently. The model and methods provided highlight the inadequacies of the healthcare system burdening the patients.

2 Methodology

2.1 Model Overview

We utilize the python libraries numpy, pandas, matplotlib, and seaborn to simulate bargaining interactions as an ultimatum game. The ultimatum game is a classical model in which there are two players who must determine how to divy up a limited amount of resources. The proposer suggests a way to split the money among itself and the responder. The responder either accepts or rejects the offer. If the responder accepts, the resources are allocated as stipulated. If the responder rejects, neither party receives anything.

The simulation considers various factors such as hospital capacity, quality, cost per service, insurance company client count, average premium, and procedure coverage. We generate synthetic data using certain assumptions (limitations discussed in the conclusion) and incorporate evolutionary game theory by basing the negotiations on the Nash equilibrium concept. Hospitals and insurance companies consider the conditions and then make offers and counteroffers. A round of the game simulates the negotiation process. This model provides insights into healthcare bargaining and allows for flexibility to alter parameters and values to simulate an array of scenarios. We include a variety of factors for a realistic representation. The simulation allows for time and cost efficient analysis as well. Below, we describe the logical flow of the algorithms and simulation.

2.2 Assumptions

We start with a scenario in which there is a certain number of patients who are in need of C-section services, providers who offer these services, and insurance companies which provide reimbursement. The variables hospital_count, insurance_company_count, patient_count, and max_rounds represent the number of hospitals, insurance companies, patients, and negotiation rounds respectively. We assume that there are more hospitals than insurance companies, although this can vary depending on region. We also assume there are 10,000 patients and we set a maximum of 50 rounds. We can adapt these variables as necessary to simulate different scenarios. Thus, the assumptions allow us to control the scale and complexity of the simulation to form foundations for our study.

2.3 Data Generation

Next, we set up data generators. These functions create randomized data frames for hospitals, insurance companies, and patients.

Each data generator takes an integer, n, as a parameter. Each hospital is characterized by the attributes capacity, quality, cost per service, and treatment availability. The capacity for each hospital is a random integer between 200 and 500. We set quality between 5 and 9. The cost per service is minimum $6,241 and maximum $60,584. Treatment availability is represented with 1 meaning available and 0 meaning unavailable. We randomly choose with a 30% probability that the treatment is unavailable and a 70% probability that the treatment is available.

For insurance companies, we generate values for client count, average premium, and coverage. We randomly select a number of clients between 900,000 and 8,000,000. The average premium is between $350 and $7,000. There is a 50% chance that the insurance company covers C-section procedures and 50% chance that the company does not.

The patients, who represent the demand side, include the attributes insurance company, the need for services, out-of-pocket cost (initially set to NaN), wait time (initially set to NaN), welfare (initially set to NaN), preferred hospital, decision, and round count. We select whether or not a patient needs services with a 40% probability that the patient needs the service and 60% otherwise. We randomly select a hospital among those available.

We call the data generators to produce the initial data and store it in the data frames. We utilize the variables hospital_count, insurance_company_count, and patient_count as parameters for the generators. These data frames are the starting point for the simulation and contain the information necessary to simulate the negotiation and transaction processes. The data generators aim to create diverse information which simulate realistic interactions within the healthcare system. We utilize real-world statistics from the American Hospital Directory [9], The Wall Street Journal [10], The California Healthcare Almanac [11], and ValuePenguin [12]. Although we base our study on a regional specific area of California, the parameters are flexible and may be adapted to the necessities of different research. Thus, there is an opportunity for extensive and robust studies of various regions.

2.4 Offer, Counteroffer, and Decision Processes

We then create the functions make_offer, make_counteroffer, and make_decision which help define the crucial conditions that will affect the negotiations. After considering the cost per service, quality, and capacity, the hospital (proposer) makes an offer to the insurance company (responder). The make_offer function calculates the value of offers that hospitals make to insurance companies. In this function, we utilize mathematical calculation to incorporate random variation. We also introduce a make_counteroffer function, which considers the offer. The calculations in make_offer and make_counteroffer are adjustable and can be customized for each situation.

After considering the offer and counteroffer, we utilize the make_decision function which takes the offer, counteroffer, hospital, insurance company, and round count as parameters. In the ultimatum game, the insurance company makes the final decision. In make_decision, if the offer is less than or equal to 90% of the counteroffer, the hospital's quality is at least 4.5, and the insurance company has clients available, the decision is set to ‘accept.’ Otherwise, the decision is set to 'reject' and we increment the round_count by 1.

2.5 Transaction Process

Upon acceptance of the offer, the transaction takes place. The transaction function takes the offer, hospital, insurance company, and patient as parameters. We reduce the hospital capacity by 1 to indicate that the patient receives treatment. We also decrement the client count of the insurance company by 1 to indicate that the company is providing services for a patient. Then, we calculate the out-of-pocket cost incurred by the patient after accepting the offer. The out-of-pocket cost is the portion of the bill that the insurance company does not cover and therefore the patient has to pay. We subtract the insurance company's average premium from the offer and check that the out-of-pocket cost is at least 0. Next, we update the wait time for the patient. If the hospital's capacity is 0, then the hospital is full and the wait time is infinity. Otherwise, the wait time equals 1 divided by the hospital capacity. Finally, we return the updated objects to reflect the changes.

2.6 Nash Equilibrium

In this game, equilibrium is reached when either all patients receive C-section services, all hospitals have reached their capacity, or the maximum number of rounds for negotiation has been reached. In this context, the Nash Equilibrium represents a stable state in the negotiation process where no player can improve their outcome by unilaterally changing their strategy given the strategy of the other player. Thus, in Nash Equilibrium neither the hospital nor insurer has incentive to deviate from their strategy after the offer, counteroffer, and decision have been made.

The nash_equilibirum function simulates the negotiation process by iterating through a given number of rounds to find the Nash Equilibrium. The function takes the hospital, insurance company, and patient as parameters. For each iteration, we first call make_offer and make_counteroffer. Following these invocations, we use make_decision to determine whether the offer is accepted or rejected. If the decision is 'accept' we call the transaction function to update values as necessary. We also calculate patient welfare as a function of hospital quality, out of pocket costs, and wait time. We return the updated status.

2.7 Game Simulation and Visual Representation

Upon setting up the Nash Equilibrium algorithm, we simulate the entire game. First, we retrieve patient and hospital information. We also check for procedure availability and check if the patient needs the service. We then check for capacity and call the nash_equilibrium function if capacity is not reached. We simulate negotiations and transactions for each patient who requires services. This continues until either the hospitals' capacity reaches the limit, or the maximum number of rounds is reached. This game thus offers insights into the complex dynamics between hospitals, insurance companies, and patients. The results may also provide invaluable predictive information regarding the outcomes of real-world negotiations.

Upon running the simulation, we output a variety of results for analysis. We provide a summary of the average welfare and wait time by insurance company, procedure coverage, hospital quality, and hospital capacity. We produce the average round count by decision. We utilize several graphics to display the results including histograms, distribution diagrams, bar charts, and scatter plots. These results are discussed in depth in the following section.

3 Results and Analysis

3.1 Results Overview

The Nash Equilibrium algorithm in our code provides information regarding how health insurance companies and hospitals will negotiate. It also shows the impact of these negotiations on the patients. The data that follows examines the negotiations which were accepted and rejected, the quality of hospitals, hospital capacity, the magnitude of coverage from insurance companies, the wait time for patients, and the welfare of patients.

3.2 Negotiations

Of the 10,000 simulated patients, 2,950 of them required a C-section, where most of the hospitals they preferred ended negotiations with the health insurance providers in the first and second rounds as shown in Figure 3.1. These results also provide insight regarding the dilemma parties often face in the ultimatum game. As many game theoretic studies reveal, players in the ultimatum game often have conflicting incentives. A proposer may make a fair or generous offer, hoping that the responder will accept, thus enabling both to obtain reward. At the same time, the proposer also yields the power to make a greedy offer to exploit the responder. However, in this study, there was a surprisingly high rate of cooperation even within the first five rounds. This then leads to the question of how factors may be altered to encourage further cooperation to benefit each party involved. We discuss the implications in further detail in Section 4.

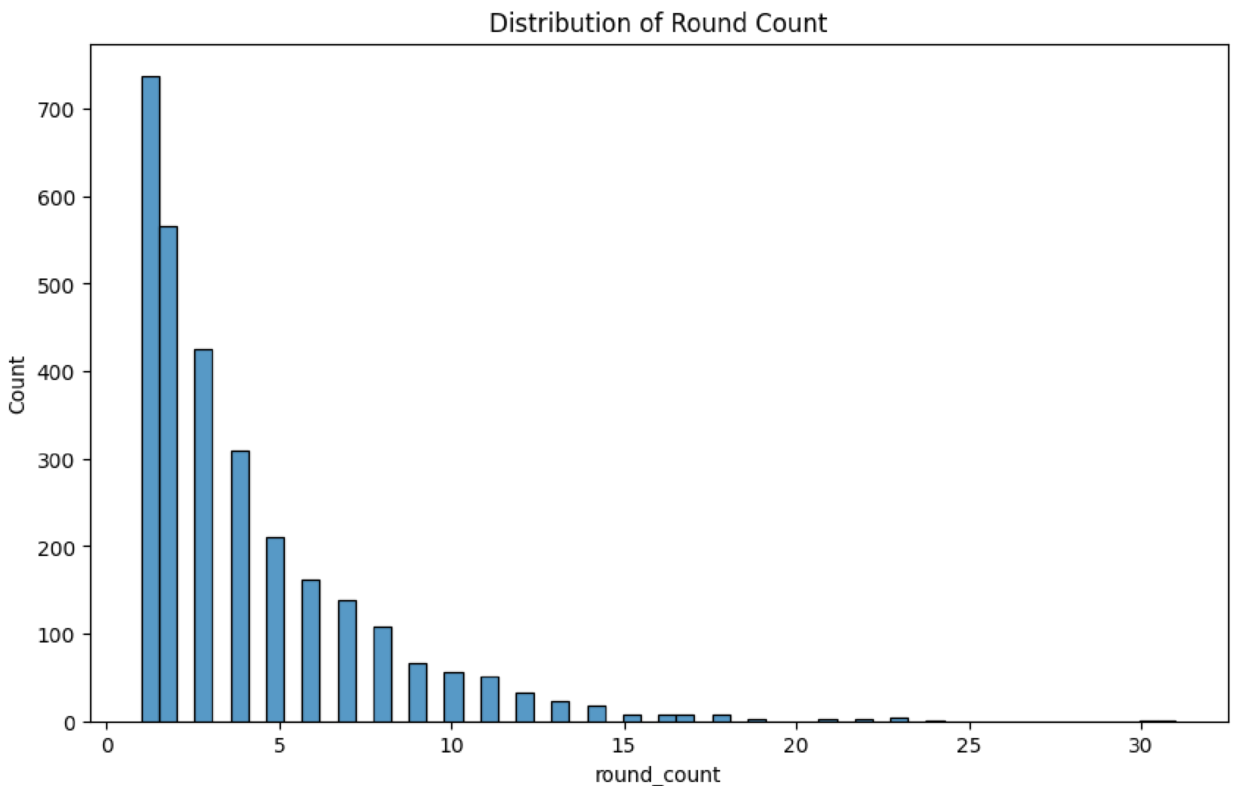

Figure 3.1

3.3 Patient Welfare

We measured average patient welfare, which we now refer to as the welfare score for simplicity, on a scale from one through ten, where the former represents no patients' needs being met and the latter represents all the patients' needs being met. All insurance companies resulted in providing patients with a welfare score in the range of 6.75 to 6.99. This can be observed in the barplot (Figure 3.2) which maps welfare to insurance companies. Insurance companies that did not provide coverage for C-sections were associated with a welfare score of 6.81, whereas those that provided coverage were associated with a welfare score of 6.88. Surprisingly, greater procedure coverage of health insurance companies only correlated to slightly higher welfare scores among the companies' corresponding patients. This is interesting because one would expect that coverage would significantly reduce financial burden and thus greatly impact welfare. Yet, other factors may affect the result as well. For instance, we have taken into account out-of-pocket costs. Thus, even if the procedure is covered, low coverage may mean that patient welfare is still low because the coverage does not alleviate financial pressure. As discussed in this section and section 3.4, hospital quality, wait times, hospital capacity, and other attributes will affect welfare. Thus, it is important to note that diagrams which consider only two factors may occlude the complexities which exist among several interconnected characteristics.

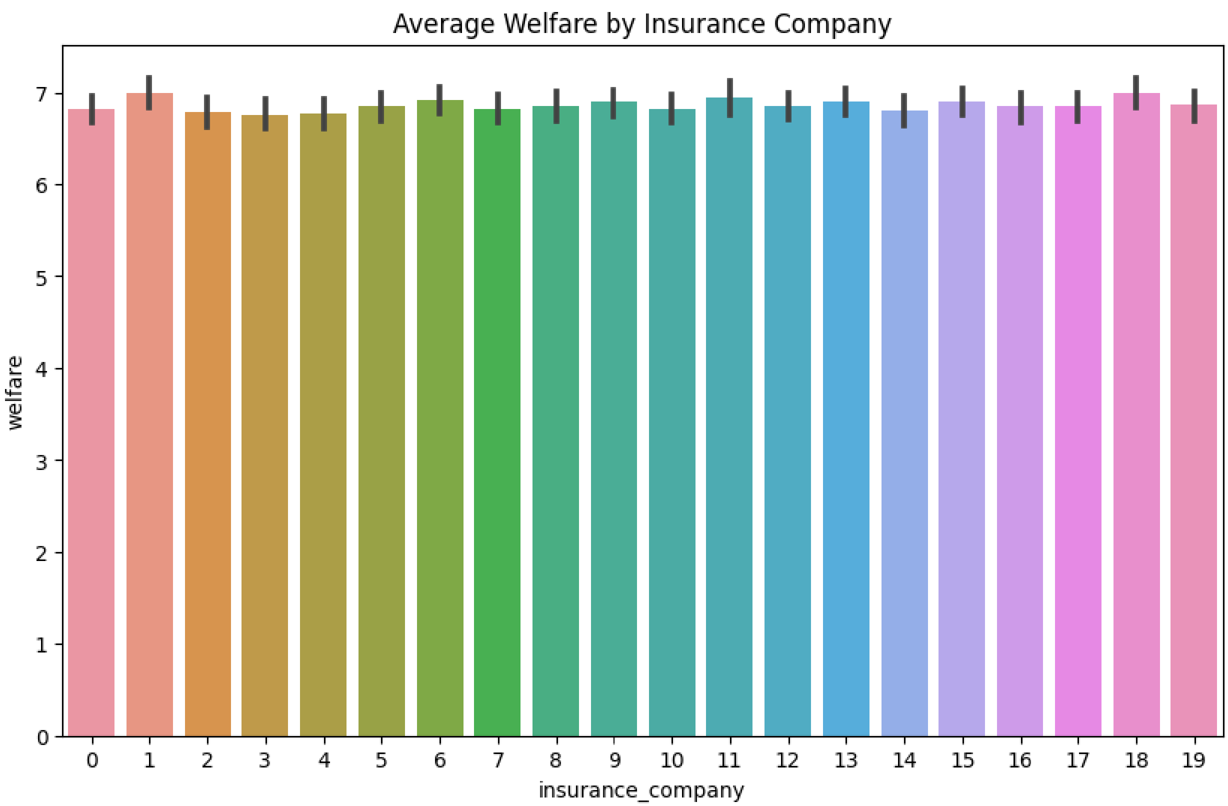

Figure 3.2

Additionally, we find that hospital quality and welfare scores are directly proportional and are nearly identical in value as well. For example, our data reveals that the lows are 5.13 for hospital quality and 5.12 for the welfare score and the highs are 8.91 for hospital quality and 8.91 for the welfare score. These scores reinforce how closely related they are to one another. Moreover, although further testing may be required, the significant difference of approximately 4 points seems to suggest that these values are not the result of chance and that they indicate a trend.

We also plot a histogram of welfare (Figure 3.3) with the number of patients on the y-axis and the welfare on the x-axis. The distribution appears to be bimodal with one peak around 5.75 and another at 7.25. The bin with the greatest number of patients has a welfare of 7.25. Evidently, it appears that patient welfare is suboptimal. Ideally, we would want to see a distribution that is skewed left, meaning that the majority of patients would be on the higher end of the patient welfare scale. The bimodal distribution may be the result of high out-of-pocket costs, long wait times, or low hospital quality. Patients will not be satisfied with excessively high prices and long wait times can result in increased complications and pain. Inadequate resources may reduce hospital quality which can then impact patient welfare. Additionally, the negotiations between the hospitals and insurance companies may have resulted in low welfare scores. For instance, if each party prioritizes profit, as is the case in real-life, patient welfare is left at the periphery and thus neglected. These results provide insight into the need to improve coverage, reduce costs, decrease wait times, and increase quality. Lastly, the welfare scores varied greatly with regard to hospital capacity, so there is little to no correlation between the two factors. This is an interesting result as we would expect that capacity would affect access to care and wait times, and thus impact welfare. Once again limitations of the study and confounding variables may factor into this result.

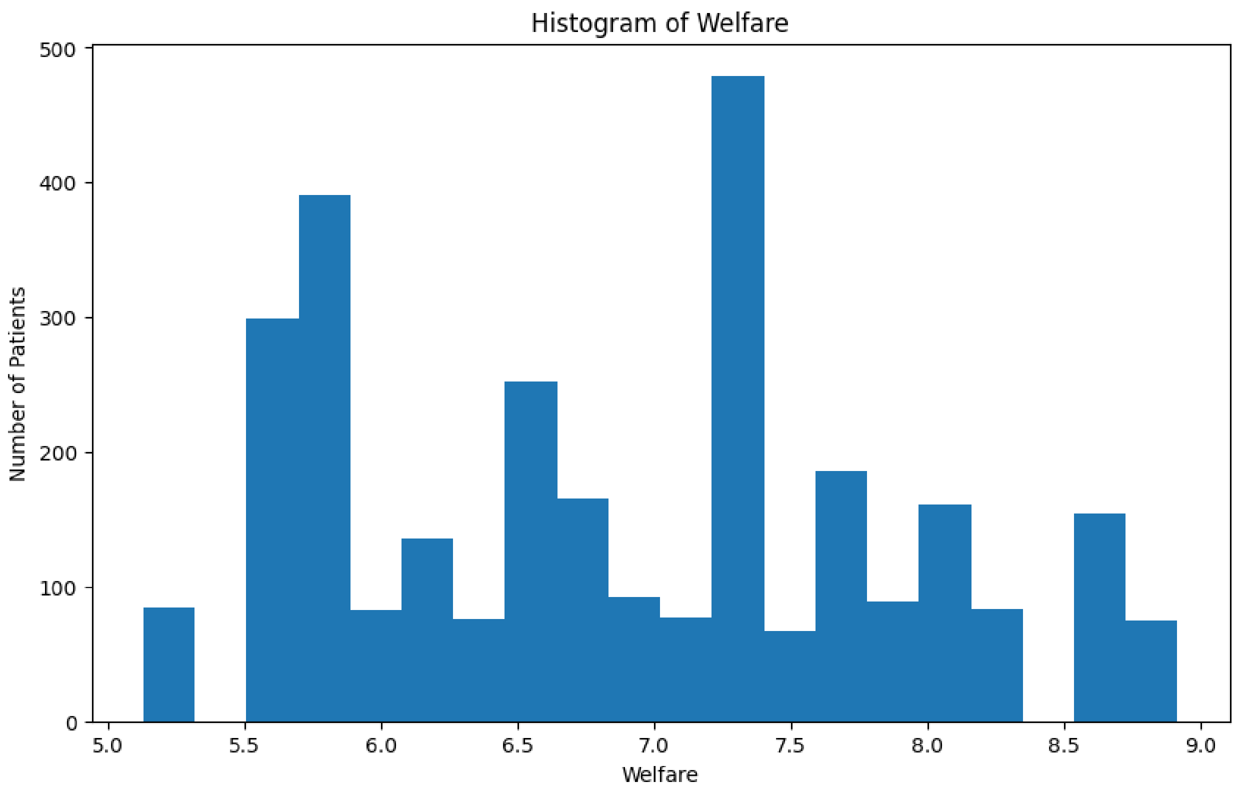

Figure 3.3

3.4 Patient Wait Time

We measured average patient wait time, which we now refer to as the wait time for simplicity, as a decimal, for which a lower value means a shorter waiting time and vice-versa. The findings show that coverage had little impact on wait time, where providing coverage had a wait time of 0.003753 and not providing coverage had a wait time of 0.003708. It is interesting to consider how insurance coverage and wait times are related. It would be expected that access to coverage would result in significantly shorter wait times. This is because the reimbursement from insurance companies provides financial incentive for hospitals to complete a procedure. In contrast, if the patient bears the entire burden of paying the bill, hospitals become concerned about defaults on bills and thus are less incentivized to provide timely treatment.

There was little to no correlation between hospital quality and wait time. This discovery is also surprising. One would assume that hospital quality and wait time would be inversely proportional with better quality reducing wait times. This is because hospitals with higher quality would be more equipped to allocate resources as needed, have better organizational skills, and have more healthcare professionals available to treat patients. Yet, there may be other confounding factors which lead to this result. For instance, if a hospital has better quality this might mean that the hospital then becomes more desirable for patients. Thus, the increased demand may put a strain on the resources. However, there was an inversely proportional correlation between hospital capacity and wait time. These findings may be a result of how the wait time is factored. Future research may find ways of incorporating hospital quality into the model for new findings.

3.5 Discussion

Thus, the data summaries and visualizations provide insight into the healthcare bargaining process and lead to several unexpected results. It would also be interesting to consider creating more visuals for the factors involved. These plots could include finding the relationship between out-of-pocket costs and welfare, capacity and quality, preferred hospital and quality, average premium and welfare, and other combinations of factors. Moreover, the inclusion of additional attributes may provide deeper revelations regarding the study. For instance, we could include a distinction between types of plans such as Healthcare Maintenance Organizations (HMOs), Preferred Provider Organizations (PPOs), Exclusive Provider Organizations (EPOs), Medicare, Medicaid, or High Deductible Health Plans (HDHPs). We could also consider the insurance company or provider reputation as some have better reputations than others.

It would be interesting to include other players such as the government to consider government regulation. The government can set guidelines which force hospitals and insurance companies to be more transparent and thus take accountability. Government regulation can also ensure patient safety. Moreover, there are other stakeholders in the negotiation process such as employers, pharmaceutical companies, unions, advocacy groups, and researchers who can affect healthcare bargaining. For instance, many people receive healthcare plans through employers. These employers thus help dictate the terms of negotiation. Moreover, pharmaceutical companies provide necessary drugs to hospitals which impacts the overall cost of care.

We could consider analyzing welfare by dividing categories into patient age and other demographics and take into account the number of employees at each hospital. There is also the question of technological advances and how they will affect bargaining. This factor could be included as well. We should also consider the amount of information available to parties in bargaining scenarios. Each party in the negotiation may or may not have access to certain information regarding payoffs, strategies, and other factors. This will influence the decision making process. In the real-world it is impossible to be omniscient. Expanding the scope of the study, we could also consider private versus public health insurance.

We could also attempt to add to the results using more complex statistical methods. Some of the values obtained from the simulation are ambiguous and it is difficult to discern whether or not perceived differences are actual trends or just the result of natural variation and chance. For instance, we could utilize a Chi-squared test which checks for association between two variables.

There is also analysis of variance (ANOVA) which compares variances among different groups. A T-test compares the means of samples and may also reveal trends and significance.

4 Implications, Further Analysis and Discussion

By analyzing simulation results, policymakers can gain new information regarding bargaining strategy, resource allocation, and policy reform that can lead to higher benefit for all parties involved. Furthermore, hospitals and insurance companies can utilize the data to navigate the intricacies of the system in order to improve bargaining outcomes. We explore the implications of the simulation code on policy considerations, access to healthcare information, quality, patient outcomes, C-section costs, the actions of each party involved, maternal mortality rate, and the broader healthcare system. Ultimately, we, as people who rely on the healthcare system, are primarily concerned with patients who are at the core of the system. These implications will allow patients to better understand the complexities of the healthcare field and thus advocate for themselves and participate in discourse to enact reform.

4.1 Policy Considerations, Patient Outcomes, and Costs

As the New York Times [1] notes, there has been an air of secrecy surrounding healthcare negotiations and pricing. This has enabled both hospitals and insurance companies to exploit consumers. Hospitals make false claims regarding discounts and patients are unable to discern the truth because baseline pricing is unavailable. This opaque system also leads to skepticism among the parties involved and therefore disincentivizes insurance companies to cooperate. The simulation code provides transparency, thus creating a platform for policymakers to test the efficacy of various policy interventions. For instance, policymakers could tune the parameters to simulate the impact of implementing regulations which incentivize care that focuses on patient welfare by making rewards contingent upon positive patient outcomes. This new information also enables patients to make more informed decisions.

Policy makers could also examine other patient-related variables, such as out-of-pocket costs, wait times, and demographics. The simulation may be expanded to assess the impact of negotiation outcomes on patients' financial burdens and access to timely care. This information can guide policy considerations aimed at promoting cost containment and affordability of C-section procedures, thus mitigating disparities in the healthcare system. Therefore, there are many opportunities for patients to benefit from this study.

4.2 Maternal Mortality Rate

When analyzing background information to conduct this study, the connection between C-sections and maternal mortality raised concerns and questions. Maternal mortality rates are a major indicator of maternal healthcare quality. The United States has a concerningly high maternal mortality rate. As NPR [13] notes, in 2021 the US maternal mortality rate was 32.9 deaths per 100,000 live births. This is more than 10 times the rate in countries such as Australia, Japan, and Spain. Inefficient allocation of resources due to suboptimal negotiations may contribute to these outcomes. By analyzing reimbursement structures and negotiations surrounding C-section procedures, providers, insurance companies and policymakers can work to reduce maternal mortality and increase quality of care.

4.3 Actions of Parties Involved

For hospitals, the new data can allow them to reflect on their bargaining approaches to maximize the reimbursement they receive. Hospitals can utilize the study to adapt their resource allocation methods and compare data to demand fair compensation. Better management of costs can increase access to staffing, equipment, and specialized services. Thus, by strategically managing C-section costs, hospitals can ensure their own profit while simultaneously maintaining quality care for patients.

Insurers can also benefit from the study. The simulation helps insurers untangle the web of factors related to bargaining to then recognize opportunities to maximize profit while also developing reimbursement models that lead to high-quality C-section care.

4.4 The Broader Healthcare System

The results of this study have implications for both C-section care and healthcare in general. People are faced with a myriad of issues including renal disease, heart disease, cancer, and other severe complications. The methods in our study can be tweaked and expanded to conduct case studies for each specific scenario and shed light on many aspects of the healthcare field. In a society where more health-related issues are arising due to pollution, pandemics, an aging population, climate change, and other factors, this information will be invaluable.

Conclusion

We used a simulation to collect accurate data on the outcome of numerous negotiations between insurance companies and hospitals pertaining to the cost and availability of C-sections. With health insurance costs rising exponentially, affordable healthcare has become inaccessible for countless people. As a result, patients forgo necessary medical treatments. This puts patients in danger and when health concerns are not treated, it often leads to worsened health conditions. It is essential to understand why costs are rising and find ways to remedy this issue.

We obtained our results by implementing the Nash Equilibrium within our code. This allowed us to identify whether the hospital and insurance company came to an agreement or disagreement. Through this simulation we found that 2,950 out of 10,000 patients required a C-section. Most of the hospitals ended negotiations with the health insurance providers in the first and second rounds. There was also a surprisingly high rate of cooperation, although there is certainly room for improvement. However, typically in the ultimatum game, a proposer wants to get as much as they can out of the responder and vice versa. With greed being a difficult factor to remedy, it makes sense that insurance costs continue to rise. Another statistic tested in the study is patient welfare. Welfare scores were mediocre, with all health insurance companies having patient welfare between 6.75 to 6.99 on a scale out of ten (ten being most cared for).

A crucial limitation of our study is data. Since we generate synthetic data through assumptions, we can not be entirely confident in our findings. The data we used was created from a simulation coded out of assumptions. In order to run the simulation, we were required to assume the ratio of hospitals to insurance companies in each region, number of patients in each region, the complexity of each situation at hand, the decisions made by opposing parties, and more. We assumed values as best we could, but there is a level of inaccuracy within the data that we must be cognizant of when analyzing it.

Another limitation that prohibits us from finding the most accurate data is time. We would like to continue testing data and find more accurate statistics through a wider pool of tests. We would also analyze the results further by dividing statistics into categories: age, region, economic status, etc., but due to the time constraint, we were unable to do so. Additionally, the government is a factor that we failed to include within our study due to the complexity of its involvement. Governments are able to enforce treatment and set restrictions for hospitals and health insurance companies. These restrictions often decrease the cost of healthcare and help uninsured and insured patients alike to acquire care. We can assume government involvement impacts the test results in a positive way, aiding more patients in getting the health services they require.

Our findings highlight the extreme inefficiencies within the healthcare system. Too many patients are in need of treatment but are unable to receive it due to economic, resource and time constraints. We must take our findings and make them available to those around us in order to raise awareness of the disparities and inefficiencies among the healthcare system in relation to insurance companies.

Further Readings

As discussed, our model is limited in scope and does not fully address the complexities of healthcare dynamics in the healthcare market. It also fails to employ more complex techniques to model the simulation such as Q-learning or Monte Carlo methods. Moreover, further research could be completed regarding the impact of healthcare pricing on individuals. We conclude our discussion with further readings to frame our study in a broader context and to gain a better understanding of the myriad of factors which our study oversimplifies. Thus, there is the opportunity to expand upon our research in the future in order to address the current limitations.

1. Bernstein, J. (2020). Not the Last Word: Surprise Medical Bills are Hardly Charitable [14]

This article discusses the impact of healthcare bills on patients and thus expands upon why the results of our study are important for motivating change in the real-world. Bernstein discusses the detrimental effects of surprise medical bills which often impose financial burden upon patients and their families. Bernstein discusses the need for legislation and reform to protect consumers.

2. Montero, A. et al. (2022). Americans' Challenges with Health Care Costs [15]

The authors address a variety of statistics regarding the struggles Americans face due to high healthcare costs. They also address the disparities among different demographic groups. The article summarizes findings from surveys and discusses the fact that both the insured and uninsured face challenges with healthcare debt and costs which prevent patients from seeking necessary care.

3. Cutler, D.M., & Zeckhouser, R.J. (1999). The Anatomy of Health Insurance [16]

Cutler and Zeckhouse explore the healthcare system in depth. Their analysis addresses the principles of insurance, moral hazard, supply and demand, the relationship between parties involved, equilibria states, adverse selection, uncertainty, health outcomes, and a myriad of other topics. Thus, this reading provides a comprehensive overview of the healthcare market.

4. Enthoven, A.C. (1988). Theory and Practice of Managed Competition in Health Care Finance [17]

Enthoven also rigorously analyzes economic concepts related to healthcare competition in order to propose solutions for promoting equity and efficiency in healthcare. Enthoven begins by discussing public policy and then delves into the organization of the medical system in a financial context. The third lecture deals with managed competition and is followed by a fourth lecture discussing the dynamics of the system. Enthoven strives to address market failures and mitigate them. Thus, this reading provides insight into how to improve healthcare delivery.

5. Trish, E., & Herring, B. (2015). How do health insurer market concentration and bargaining power with hospitals affect health insurance premiums? [18]

The authors state that the healthcare industry is highly concentrated, meaning that a small number of insurance companies control the majority of the market which gives these companies unfair leverage in negotiations. The authors find that high market concentration has a direct impact on insurance premiums. This provides insight into factors which can be adapted through policy change to lower healthcare costs.

6. Güth, W. et al. (1982). An Experimental Analysis of Ultimatum Bargaining [19]

This paper focuses on bargaining situations with two players and two stages. The research touches upon topics such as complete versus incomplete information, perfect information, strategic asymmetry, and equilibrium. It thus provides more background information into the dynamics of bargaining.

7. Zhou, Yi. et al. (2014). Evolution With Reinforcement Learning in Negotiation [20]

The research focuses on utilizing reinforcement learning to analyze negotiations. The methodology uses the reinforcement learning algorithm in conjunction with replicator dynamics to study behaviors displayed during negotiations. The model provides deeper insight into the various ways we can analyze negotiations and thus sets the stage for enhanced studies in the future.

References

[1] "Consumer price index for all urban consumers: Medical care in U.S. city average," FRED, May 27, 2023 https://fred.stlouisfed.org/series/CPIMEDSL (accessed May 27, 2023).

[2] J. Katz and S. Kliff, "Hospitals and Insurers Didn't Want You to See These Prices. Here's Why.," *The New York Times*, New York City, Aug. 22, 2021 https://www.nytimes.com/interactive/2021/08/22/upshot/hospital-prices.html

[3] L. Small, "Study: In Healthcare Price Negotiation, Insurer Size Matters," Fierce Healthcare, January 10, 2017 https://www.fiercehealthcare.com/payer/study-when-negotiating-healthcare-prices-insurer-size-matters (accessed May 26, 2023).

[4] D. Goldhill, "Opinion | In Health Care, America is the World's Indispensable Nation," The Washington Post, November 29, 2022 https://www.washingtonpost.com/opinions/2022/11/29/us-health-care-expensive-indispensable-nation/ (accessed May 23, 2023).

[5] J. Fields, "Hospitals want price hikes. how should insurers respond?," Oliver Wyman Impact-Driven Strategy Advisors, https://www.oliverwyman.com/our-expertise/perspectives/health/2022/jun/hospitals-want-price-hikes--how-should-insurers-respond-.html (accessed May 22, 2023).

[6] E. Rivelli, "How much does it cost to have a baby? 2023 averages," Forbes, March 1, 2023 https://www.forbes.com/advisor/health-insurance/average-childbirth-cost/#:~:text=How%20Much%20Should%20You%20Expect,to%20%243%2C214%20for%20cesarean%20births (accessed May 23, 2023).

[7] W. H. Sandholm, "Evolutionary Game Theory," SpringerLink, 2009 https://link.springer.com/referenceworkentry/10.1007/978-0-387-30440-3_188#:~:text=Evolutionary%20game%20theory%20studies%20the,decision%20rules%20by%20individual%20agents (accessed May 24, 2023).

[8] J. McKenzie Alexander, "Evolutionary Game Theory," Stanford Encyclopedia of Philosophy, January 14, 2002 https://plato.stanford.edu/entries/game-evolutionary/ (accessed May 22, 2023).

[9] "American Hospital Directory - Individual Hospital statistics for California," ahd.com - American Hospital Directory, https://www.ahd.com/states/hospital_CA.html (accessed May 23, 2023).

[10] A. Wilde Mathews, T. McGinty, and M. Evans, "How Much Does a C-section Cost? At

One Hospital, Anywhere From $6,241 to $60,584.," The Wall Street Journal, February 11, 2021 https://www.wsj.com/articles/how-much-does-a-c-section-cost-at-one-hospital-anywhere-from-6-241-to-60-584-11613051137 (accessed May 23, 2023).

[11] "California Health Insurers: Large Insurers Remain on Top," California Health Care Foundation. (2019, May). California Health Insurers Almanac 2019. [Online]. Available: https://www.chcf.org/wp-content/uploads/2019/05/CAHealthInsurersAlmanac2019.pdf

[12] S. Guinan, "Best Cheap Health Insurance in California 2023 ," ValuePenguin, May 25, 2023 https://www.valuepenguin.com/best-cheap-health-insurance-california (accessed May 26, 2023).

[13] S. Simmons-Duffin and C. Wroth, "Maternal deaths in the U.S. spiked in 2021, CDC reports," NPR, March 16, 2023 https://www.npr.org/sections/health-shots/2023/03/16/1163786037/maternal-deaths-in-the-u-s-spiked-in-2021-cdc-reports#:~:text=The%20U.S.%20rate%20for%202021,deaths%20per%20100%2C000%20in%202020 (accessed May 24, 2023).

[14] J. Bernstein, "Not the last word: Surprise medical bills are hardly charitable," Clinical orthopedics and related research, October 2020 https://www.ncbi.nlm.nih.gov/pmc/articles/PMC7491885/ (accessed May 22, 2023).

[15] A. Montero, L. Hamel, M. Brodie, and A. Kearney, "Americans' challenges with health care costs," KFF, July 14, 2022 https://www.kff.org/health-costs/issue-brief/americans-challenges-with-health-care-costs/ (accessed May 20, 2023).

[16] D. Cutler and R. Zeckhauser, *The Anatomy of Health Insurance*, 1999. doi:10.3386/w7176

[17] A. C. Enthoven, "Theory and practice of managed competition in Health Care Finance," Theory and Practice of Managed Competition in Health Care Finance - 1st Edition, June 1, 1988 https://www.elsevier.com/books/theory-and-practice-of-managed-competition-in-health-care-finance/enthoven/978-0-444-70359-0 (accessed May 23, 2023).

[18] E. E. Trish and B. J. Herring, "How do health insurer market concentration and bargaining power with hospitals affect health insurance premiums?," Journal of health economics, July 2015 https://pubmed.ncbi.nlm.nih.gov/25910690/ (accessed May 24, 2023).

[19] W. Güth, R. Schmittberger, and B. Schwarze, "An experimental analysis of ultimatum bargaining," Journal of Economic Behavior & Organization, December 1982

https://www.sciencedirect.com/science/article/pii/0167268182900117 (accessed May 23, 2023).

[20] Y. Zou, W. Zhan, and Y. Shao, “Evolution with reinforcement learning in negotiation,” PLOS ONE, July 21, 2014 https://journals.plos.org/plosone/article?id=10.1371%2Fjournal.pone.0102840 (accessed May 20, 2023).