Hospital Cost Efficiency Analysis

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Abstract

Throughout the years, the citizens of the United States has experienced a steady increase in the cost of their healthcare. According to the Centers for Medicare & Medicaid Services [93], in 2021, healthcare costs skyrocketed to $4.3 trillion [Figure 1]. The American Medical Association revealed that the United States spends more on healthcare than any other country in the world, with costs approaching 18% of the gross domestic product (GDP) [1]. The cost of healthcare is driven by many confounding factors such as the economy of the market that the hospital is operating in, natural disasters, and waste just to name a few. The diverse nature of those factors makes researching the cost of healthcare a complex issue. Fortunately, many scholars before us have researched and analyzed the problem. The Institute of Medicine, Berwick, and Hackbarth, have identified six domains of waste that are said to have a direct impact on the cost of healthcare. Hence reducing the cost of any of those six domains, we may be able to reduce the cost of healthcare [2]. Those six domains of waste are failure of care delivery, failure of care coordination, overtreatment or low-value care, pricing failure, fraud and abuse, and administrative complexity. Administrative complexity is the most tangible and measurable of the six domains of waste, hence, we focus on waste, which is related to administrative complexity. We define administrative complexity cost as the needed expenses of a hospital for its day-to-day operations. We assumed that hospitals that provide the same type of service (hospital type) and are relatively similar in size, (number of beds, employees) shouldn't have too much of a variation when it comes to their administrative complexity cost. As such, our objective for this paper is to use Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) to model an efficiency score for each hospital in our Centers for Medicare & Medicaid Services (CMS) data.

We will use the mean method used by Haney and Pollitt [94] to combine the results from DEA and SFA for each hospital and generate a final efficiency score for each hospital. With the combined or consolidated efficiency score from both methods (DEA and SFA), we will identify hospitals with low-efficiency scores, hospitals with average efficiency scores, and hospitals with high-efficiency scores. We also hoped to gain a deeper understanding of the confounding variables that have a direct impact on the hospital's efficiency scores. Finally, we hope to analyze annual trends and compare the top and bottom 5 hospitals, we hope to draw a meaningful conclusion on the reason behind the efficiency scores trends and make suggestions for improvements.

Key Words: Hospitals, Efficiency, Data Envelopment Analysis, Stochastic Frontier Analysis, Administrative complexity

Introduction

Based on prior studies, approximately 30% of healthcare spending in the United States may be considered waste [1]. Those findings open the door to the idea that reducing healthcare waste may result in also reducing healthcare costs for consumers. From the 6 domains of waste that were identified by The Institute of Medicine, Berwick and Hackbarth [2], we used administrative complexity as the focal point of our analysis since it’s the most tangible and concrete to analyze. We defined administrative complexity as the cost of the administration and the operation of a hospital on a day-to-day basis. Using administrative costs, we will calculate an efficiency score for each hospital which we will use to get a deeper understanding of each hospital’s efficiency standing.

Efficiency calculation can be very complex due to the noise in the data, and many external factors. For example, natural disasters can increase or decrease the utilization rate of a hospital, a country's economic hardship or recession can decrease the utilization rate while a pandemic can have both the effect of increasing and decreasing hospital utilization. While hospital utilization is not the only factor that drives the healthcare cost, the administrative cost will fluctuate as hospital utilization increases or decreases. The more patients that are admitted, the more the hospital spends on patient record keeping, cafeteria, laundry, and staff, just to name a few administration expenses.

Due to the complexity of calculating the efficiency of the hospitals, we will be using Data Envelopment Analysis (DEA), and Stochastic Frontier Analysis (SFA) to model the efficiency score of the hospitals. DEA is a non-parametric method while SFA is a parametric method. Parametric statistics are based on assumptions about the distribution of the population from which the sample was taken while nonparametric statistics are not based on assumptions, that is, the data can be collected from a sample that does not follow a specific distribution. Cost efficiency was examined by Linna [54] who realized that the results generated by SFA and DEA are similar.

According to Haney and Pollitt [94], while both methods generate similar results, they balance each other as SFA handles data noise which DEA is not able to, in fact, none of the methods are superior, in real word application, it is regarded as "best-practice" to combine the estimates obtained from DEA and SFA. Their combined efficiency score is said to be a precise efficiency score. We used the mean method [92] to combine the efficiency score from DEA and the efficiency score from SFA. Hence using both DEA and SFA methods the hospital's efficiency scale that we calculate is sure to be more reliable and less susceptible to external factors bias.

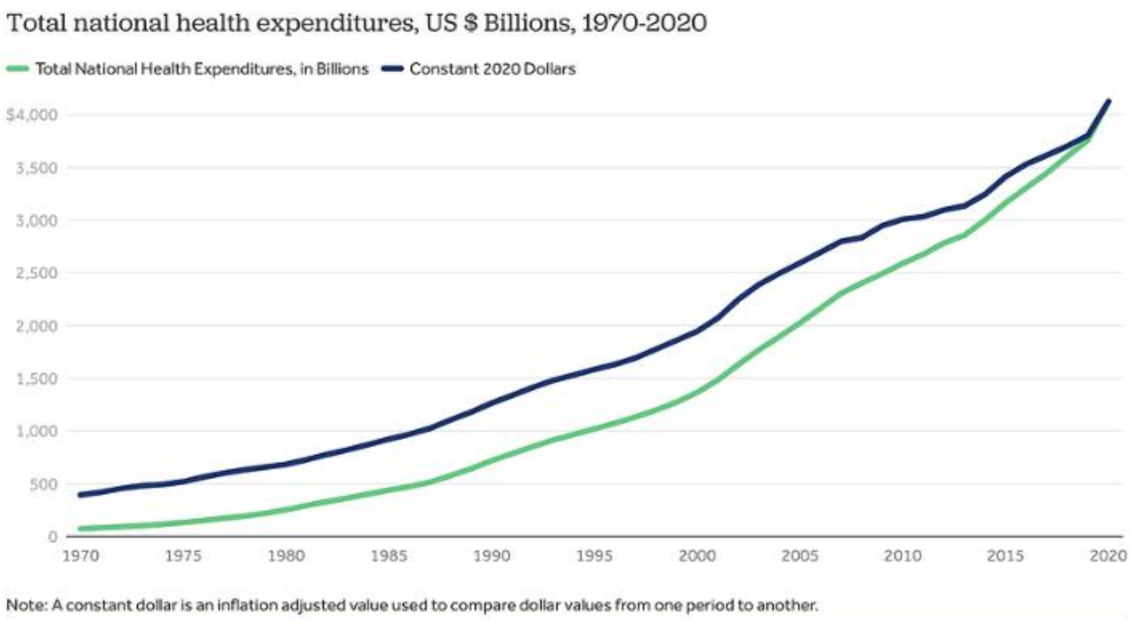

Figure 1: Increase in national health expenditure
Source KFF analysis of National Health Expenditure (NHE) data

Motivation

The United States spends the most when it comes to healthcare, close to 18% of the country's Gross Domestic Product (GDP) [1] while the cost of healthcare has been rising consistently for consumers [Figure 1]. Primary care visits and procedures that we used to pay less than $100, are now costing in the hundreds. This situation has made it hard for most Americans to meet their healthcare needs. We can look at the famous 1.1 million dollar bill sent to Michael Flor who spent 62 days with COVID-19 in a Swedish Medical Center in Issaquah [3] as an example of the consequences of the situation. While we can't prove to which degree the cost of healthcare is impacted by waste related to administrative complexity, we can safely assume that those numbers could have been less if the waste in healthcare wasn't so high. That conclusion is based on those findings by The Institute of Medicine, Berwick, and Hackbarth [2], on their research conducted on the 6 domains of waste in healthcare.

In this paper, we aim to model a hospital efficiency scale by focusing on the waste associated with administrative complexity. We use Data Envelopment Analysis (DEA), and Stochastic Frontier Analysis (SFA) to model an efficiency scale for the hospitals. Ultimately, combine the results for DEA and SFA to generate a final efficiency score for each hospital which is more reliable than the individual results. We hoped to gain a deeper understanding of the confounding variables that have a direct impact on the hospital's efficiency scores. We will analyze annual trends and compare the top and bottom 5 hospitals, to draw a meaningful conclusion on the reason behind the efficiency scores trends and make suggestions for improvements.

Methods

Dataset

In this paper, we used data from the Centers for Medicare & Medicaid Services (CMS) Hospital. More precisely the form 2552-10 WORKSHEET B-1, which is the hospital cost report. The data is from 2010 to 2021 and comes from 6802 distinct hospitals for a total of 63,435 rows. We dropped data from 2010 (2323 hospitals) and 2021 (51 hospitals) since they are incomplete and were missing about 60% of the hospitals. We are using data from 2011 to 2020 which report data for 6784 hospitals for a total of 61,061 rows and 104 columns. Our data includes administration cost information, personnel/staff, the total number of discharges, and bed records just to name a few. we are using data for the years 2011 to 2020 to calculate the efficiency of 4800 hospitals ranging from 11 different types [Table 2]. We assumed that hospitals that provide the same type of service and are relatively similar in size (bed capacity, discharges, staff) should have approximately the same expenses for their day-to-day operation or administration. After a quick look at the data, we realized that there was a lot of variation in the administrative cost for the hospitals, which reinforce our decision of using administrative complexity as a domain of waste to evaluate the hospitals in our data. Further exploration of the data, we realized hospital Type 1 which refers to general short-term hospitals have the most variation when it comes to administrative complexity cost, hence we made hospital Type 1 our focus.

You can find a full disclosure of the list of variables in the variable section. We use 23 variables [Table 1] for our input which is the summation of various administrative expense categories that range from simple building maintenance, equipment, laundry, cafeteria, acquiring organs, and patient record keeping, just to name a few. Hospitals usually deliver many services which can be seen in as many outputs as possible, fortunately, due to our data being reported at an annual header level, we can limit our output to the Number of Patients (Admission), Number of Beds, Number of Inpatient Discharges, Number of Outpatient Discharges. We can have 1 input if we use the total administrative cost or up to 104 inputs if we use the different variables that make the total administrative cost separately. Overall, we have 23 inputs [Table 1] and 4 outputs. All our variables are statistical variables.

Table 1: presents a descriptive analysis of the data.

Usage	Variable/Column name
Input	1 Capital Related Costs-Buildings and Fixtures
	2 Capital Related Costs-Movable Equipment
	4 Employee Benefits Department
	5 Administrative and General
	6 Maintenance and Repairs
	7 Operation of Plant
	8 Laundry and Linen Service
	9 Housekeeping
	10 Dietary
	11 Cafeteria
	12 Maintenance of Personnel
	13 Nursing Administration
	14 Central Services and Supply
	15 Pharmacy
	16 Medical Records & Medical Records Library
	17 Social Service
	18 Other General Services (specify)
	19 Nonphysician Anesthetists
	20 Nursing Program
	21 Intern & Res. Service-Salary & Fringes (Approved)
	22 Intern & Res. Other Program Costs (Approved)
	23 Paramedical Education Program (specify)
Output	1 Number of Patients (Admission)
	2 Number of Beds
	3 Number of Inpatient Discharges
	4 Number of Outpatient Discharges
Output	Total Discharges

CMS Hospital form 2552-10 WORKSHEET B-1
Link Data set : https://www.cms.gov/Research-Statistics-Data-and-Systems/Downloadable-Public-Use-Files/Cost-Reports/Hospital-2010-form

The raw data was obtained in SAS format and had to be converted to CSV before the validation and staging process. The raw data is a consolidation of various CMS forms for a total of 5520 variables or columns and 63,435 rows for 6802 Hospitals. The variables can be grouped into Hospital salary cost, Hospital maintenance cost, Hospital administrative cost, Hospital hours worked, and various other report forms that are provided by CMS, such as Worksheet S, Worksheet A, Worksheet B Part I, Worksheet C Part I, Worksheet D Part I, Worksheet E Part A, Worksheet G, Worksheet H, Worksheet I-1, Worksheet J-1 Part I, Worksheet K,   Worksheet L Parts I, II & III, Worksheet M-1, Worksheet N-1, Worksheet O.

Table 2: Hospital type code and description

Hospital Type Code	Hospital Type Code Description
1	General Short Term
2	General Long Term
3	Cancer
4	Psychiatric
5	Rehabilitation
6	Religious Non-Medical Health Care Institutions
7	Children
8	Alcohol and Drug
9	Other
10	Extended Neoplastic Disease Care
11	Indian Health Service

After validation and staging, we removed data from 2010 and 2021 and are left with 61,061 rows and 5520 columns for 6784 Hospitals. After isolating form 2552-10 WORKSHEET B-1, we are left with 104 columns. Hospital Type 1 is the one with the highest administrative cost [Figure 2], and the highest administrative cost variation [Figure 3]. We extract all the data with a hospital type 1, and with data reported for the full-time range of 2011 to 2020, we end with a final count of 46,749 rows for 5131 unique hospitals. We also further divided the hospitals of type 1 by using their Primary Specialty, and by using their number of specialties. This allows us to further group similar hospitals with one another. We want to leverage this grouping to better understand our output. As hospitals with more complex specialties or with multiple specialties may spend a bit more on their administration, while simple specialties may spend less.

Hospitals Specialty grouping

- 1 - 2 Specialties (low Complexity)
- 3 - 5 Specialties (Moderate Complexity)
- 6+ Specialties (High Complexity)

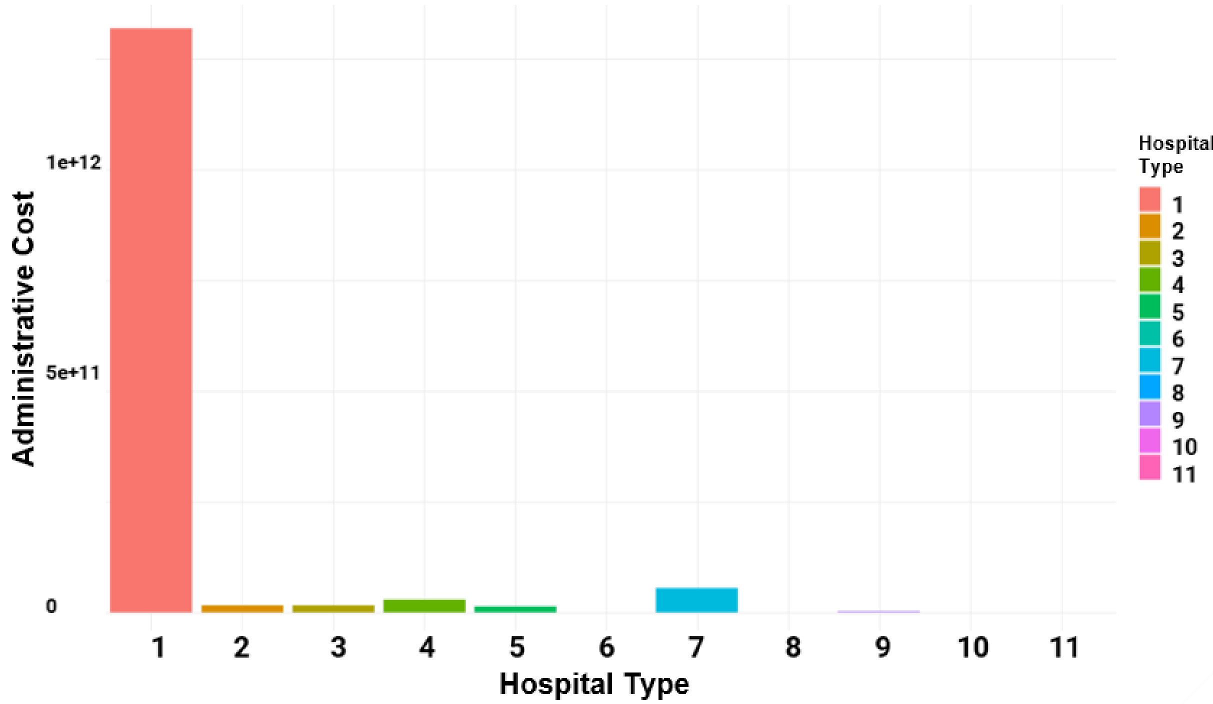

Figure 2: Administrative cost evaluation

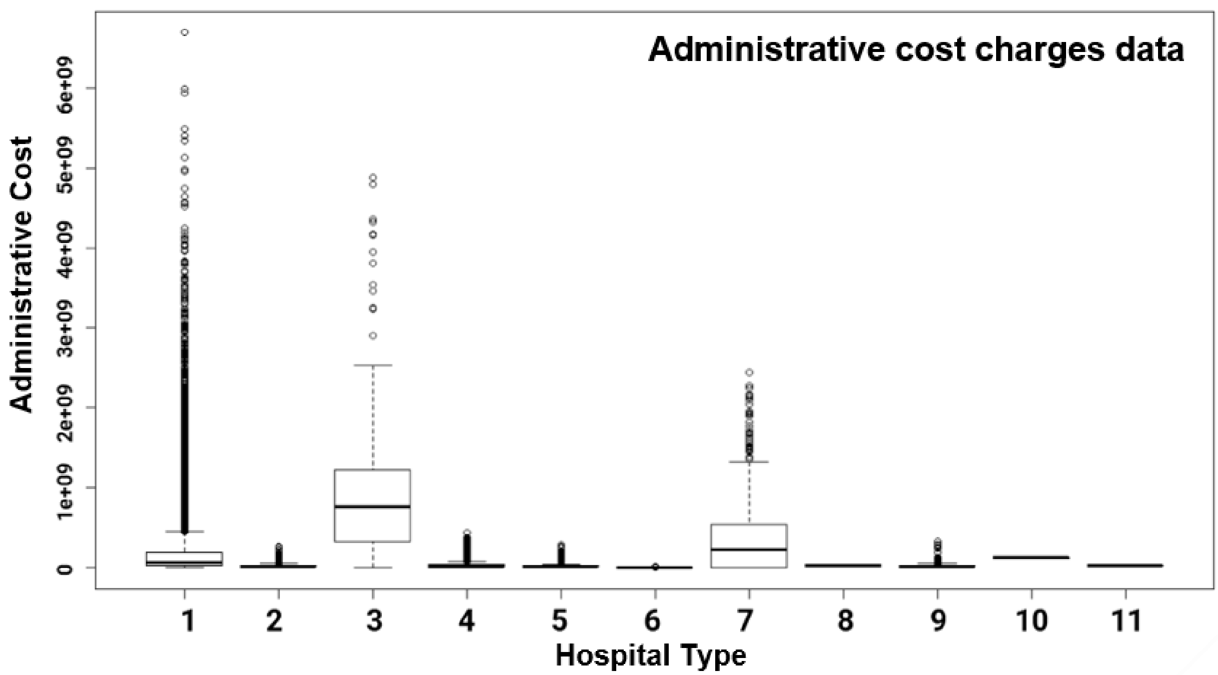

Figure 3: Hospital Administrative cost boxplot

Hospital form 2552-10 WORKSHEET B has 104 variables:

1. "New Capital Buildings and Fixtures"
2. "New Capital Equipment"
3. "Other Capital"
4. "Employee Benefits"
5. "Administrative_and_General"
6. "Maintenance and Repairs"
7. "Operation of Plant"
8. "Laundry and Linen Service"
9. "Housekeeping"
10. "Dietary"
11. "Cafeteria"
12. "Maintenance of Personnel"
13. "Nursing Administration"
14. "Central Services and Supply"
15. "Pharmacy"
16. "Medical Records and Medical Rec. Library"
17. "Social Service"
18. "Other General Service"
19. "Nonphysician Anesthetists"
20. "Nursing School"
21. "Interns & Res Salary and Fringe Benefits"
22. "Interns & Res Other Program Costs"
23. "Paramedical Education"
24. "Adults and Pediatrics"
25. "Intensive Care Unit"
26. "Coronary Care Unit"
27. "Burn Intensive Care Unit"
28. "Surgical Intensive Care Unit"
29. "Other Special Care Unit"
30. "Subprovider-IPF"
31. "Subprovider-IRF"
32. "Subprovider I"
33. "Subprovider II"
34. "Nursery"
35. "SNF"
36. "NF"
37. "ICF"
38. "OLTC"
39. "Operating Room"
40. "Recovery Room"
41. "Delivery Room and Labor Room"
42. "Anesthesiology"
43. "Radiology-Diagnostic"
44. "Radiology-Therapeutic"
45. "Radioisotope"
46. "CT Scan"
47. "MRI"
48. "Cardiac Catheterization"
49. "Laboratory"
50. "PBP Clinical Lab Services Program Only"
51. "Whole Blood & Packed Red Blood Cells"
52. "Blood Clotting Factors for Hemoph."
53. "Blood Storing, Processing, Trans"
54. "Intravenous Therapy"
55. "Respiratory Therapy"
56. "Physical Therapy"
57. "Occupational Therapy"
58. "Speech Pathology"
59. "Electrocardiology"
60. "Electroencephalography"
61. "Medical Supplies Charged to Patients"
62. "Impl. Dev. Charged to Patients "
63. "Drugs Charged to Patients"
64. "Renal Dialysis"
65. "ASC (Non Distinct Part)"
66. "Other Ancillary"
67. "RHC"
68. "FQHC"
69. "Clinic"
70. "Emergency"

71. "Observation Beds (non Distinct Unit)"
72. "Observation Beds (Distinct Unit)"
73. "Other Outpatient Services"
74. "Home Program Dialysis"
75. "Ambulance Services"
76. "Durable Medical Equipment Rented"
77. "Durable Medical Equipment Sold"
78. "Other Reimbursable"
79. "CMHC"
80. "CORF"
81. "OPT"
82. "OOT"
83. "OSP"
84. "Int & Res (non-approved teaching program"
85. "HHA"
86. "Kidney Acquisition"
87. "Heart Acquisition"
88. "Liver Acquisition"
89. "Lung Acquisition"
90. "Pancreas Acquisition"
91. "Intestinal Acquisition"
92. "Islet Acquisition"
93. "Other Organ Acquisition"
94. "Interest Expense"
95. "Utilization Review SNF"
96. "ASC (Distinct Part)"
97. "Hospice"
98. "Other Special Purpose"
99. "Gift, Flower, Coffee Shop, Canteen"
100. "Research"
101. "Physicians Private Office"
102. "Nonpaid Workers"
103. "Other Nonreimbursable"
104. "Total"

Tools and Algorithms

We will use Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) to calculate the efficiency score of the hospitals. A little background about DEA and SFA, usually the methods are used in the financial sector, nonetheless, many researchers have used them to determine hospital efficiency scores in the past [8]. They typically identify the hospital sector of operation, then calculate the efficiency associated with the healthcare units. DEA is a non-parametric method that uses math programming for efficiency calculations and estimates the efficiency of a non-parametric measurement from the uncertain frontier [70].

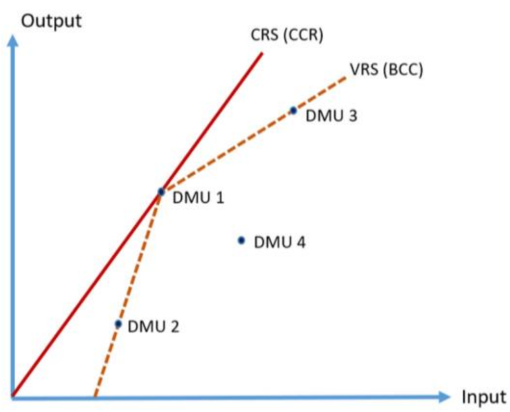

Figure 4: CRS and VRS methods of Data Envelopment Analysis (DEA)

For DEA we will use Constant Returns to Scale (CRS) which implies that output will change by the same proportion as inputs. Hence the name is constant. We will also use Variable Returns to Scale (VRS) which imply that an increase or decrease in input or outputs will not result in a proportional change in the outputs or inputs. Using those two methods will make our Data Envelopment Analysis efficiency score more reliable. Figure 4 shows a visual representation of CRS and VRS for decision-making units, in our case hospitals. With CRS the increase or decrease in scale for the inputs or outputs results in the same proportional change on the opposite side which can be the outputs or inputs respectively. In other words, the scaling of the inputs and outputs is constant. While the scaling for VRS falls under a set of possible values instead of being constant. In other words, an increase in inputs doesn't always increase outputs and vice versa [Figure 4]. This allows us to truly test hospitals and determines their optimal and ideal efficiency scores.

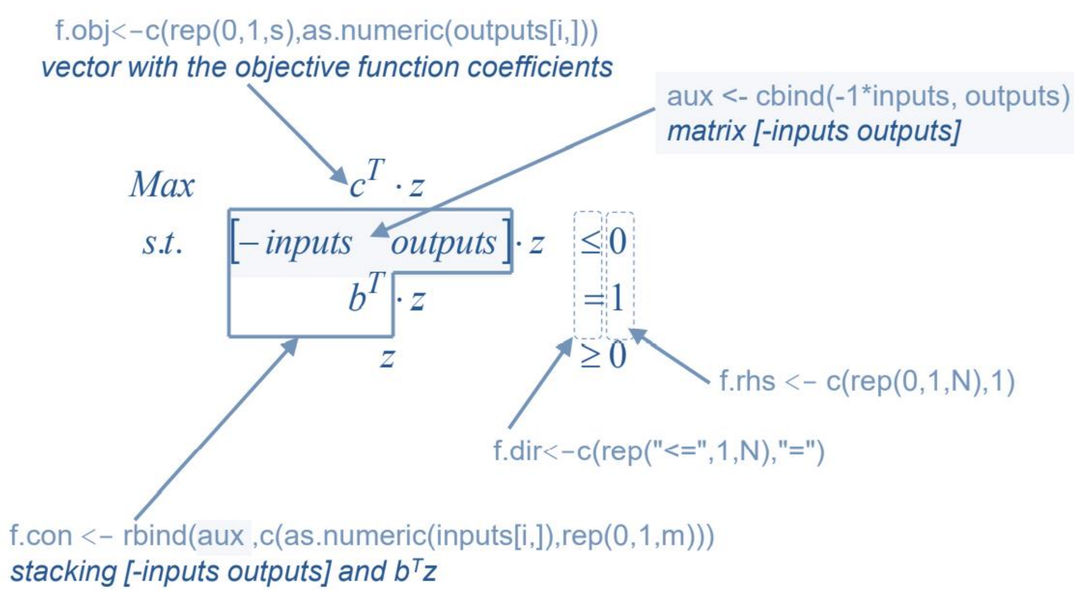

Figure 5: DEA Equation translated to R-Code

SFA is a parametric method that hypothesizes a practical form of the model in which we can use data to evaluate the decision-making units (DMUs). SFA requires the input variable to be the total costs which means that the cost efficiency is evaluated. The output should be tied to the patient’s health status. Unfortunately, the patient's health status is not easily measured and is replaced by alternative variables that represent the same result in almost all the hospital's efficiency studies. Such variables are Inpatient and outpatient discharges, admission, and bed capacity. The original formulation of the SFA model is based on the stochastic frontier production function and it can be implicitly expressed in matrix form as follow:

$$O_i = I_i\beta + \varepsilon_i \, , \forall i = 1, \ldots , n \quad (1)$$

where Ii and Oi are, respectively, the input and output vector of the i th DMU (i = 1, . . . , n), β is the vector of unknown parameters to be assessed, and εi is the composite error term. The error term is specified as the difference εi = Vi + Ui . The vector Vi is defined by random effect variables that account for the aggregate effects of unobserved factors on the production process. These factors are exogenous and cannot be controlled by the DMUs. The vector Ui consists of non-negative random variables and is introduced to account for technical inefficiency in production. This inefficiency is commonly expressed in terms of output deviations from the frontier due to factors that can be controlled by the DMUs.

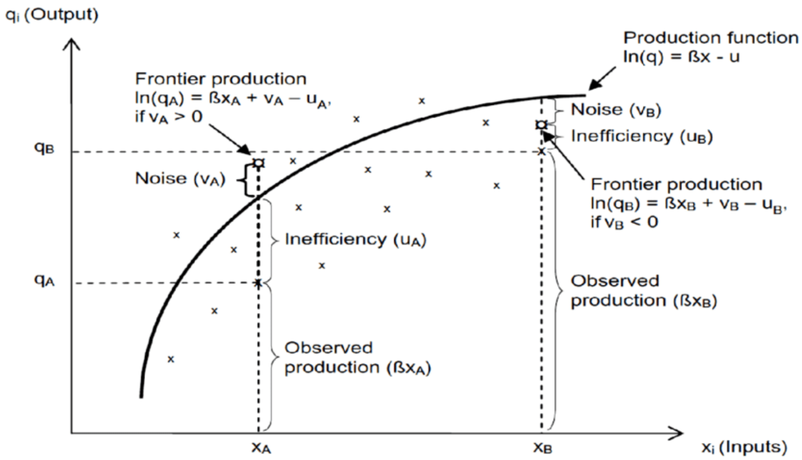

Figure 6: SFA equation

Through the years, several alternative specifications of Equation (1) have been proposed due to the variety of research areas to which the model has been applied. Nevertheless, all these specifications can be considered as particular cases of the following more general matrix equation ([74,75])

$$Oi = F(Ii ; \beta) + \varepsilon i \quad (2)$$

F(Ii ; β) is a specified production function. When evaluating how efficiency evolves over time, Equation (2) becomes as follows ([74,75]):

$$Oit = F(Iit; \beta) + \varepsilon it \quad (3)$$

where Iit and Oit are, respectively, the input and output vector of the i thDMU (i = 1, . . . , n) for the period t (t = 2, . . . , T), F(Iit; β) is the production function, β is the vector of unknown parameters to be assessed, and εit = Vit − Uit is the composite error term.

$$\varepsilon it = Vit - Uit$$

Vit represents statistical noise, that is, the effects of exogenous and uncontrollable factors that the hospitals cannot measure, such as measurement errors in the dependent variable, labor market conflicts, trade problems, access to raw material, quality, and left-out illustrative variables. Uit denotes technical inefficiency, which is, the effects of those factors which can be monitored by the hospitals.

The advantage of DEA is that compound production environments can be arranged with multiple inputs and outputs. SFA can distinguish among efficient units, but DEA has a limited ability to do this. Both techniques can distinguish inefficient hospitals [55]. The Cobb-Douglas functional formula is one of the most common applications of SFA, it applies one input or output according to environmental aspects that are examined individually. Researchers have applied these two approaches in the past to evaluate the efficiency of the US 1471 hospitals and showed the Baumol effect. Once hospitals' effectiveness declined, the trend of labor costs soars gradually.

According to Katharaki [8], both DEA and SFA approaches provide different efficiency estimates for numerous criteria such as statistical inputs and outputs definition, data availability, and noise. Nonetheless, Katharaki [8] figured out how to combine the methods to measure efficiency properly. To combine both methods, we leverage an average technical efficiency (ATE) model made up of data envelopment analysis (DEA) and stochastic frontier analysis (*SFA*) for assessing efficiency in public hospitals during the year 2011 to 2020.

The DEA method is a non-parametric method that requires no information other than the input and output quantities. *SFA* is a parametric method that considers stochastic noise in data and allows statistical testing of hypotheses about production structure and degree of inefficiency. We use these two competing approaches to balance each method's strengths, and weaknesses and get the best possible results.

Results And Discussion

The Hospital Efficiency using Data Envelopment Analysis (DEA), is assessed first. We used the 23 administrative costs variables as input and total inpatient outpatient visits/discharges, and bed capacity as output. The number of DMUs is equal to the number of rows of our data matrix (we first run with a sample of 1000 hospitals), N= 1000. The number of input variables, S = 23. The number of output variables, M = 4.

We ran the CRS, VRS, SE models and compared the results [Figure 7]. Constant returns-to-scale (CRS) reflects the fact that output will change by the same proportion as inputs are changed. For example, if the input is doubled, the output will double as well. Variable returns to scale (VRS) is a type of frontier scale used in data envelopment analysis (DEA). It helps to estimate efficiencies whether an increase or decrease in input or outputs does not result in a proportional change in the outputs or inputs respectively. The Scale Efficiency (SE) Model can be used to determine how close an observed DMU is to the most productive scale size. It may be calculated as the ratio of the measure of technical efficiency calculated under the assumption of constant returns to scale (CRS) to the measure of technical efficiency calculated under the assumption of variable returns to scale (VRS).

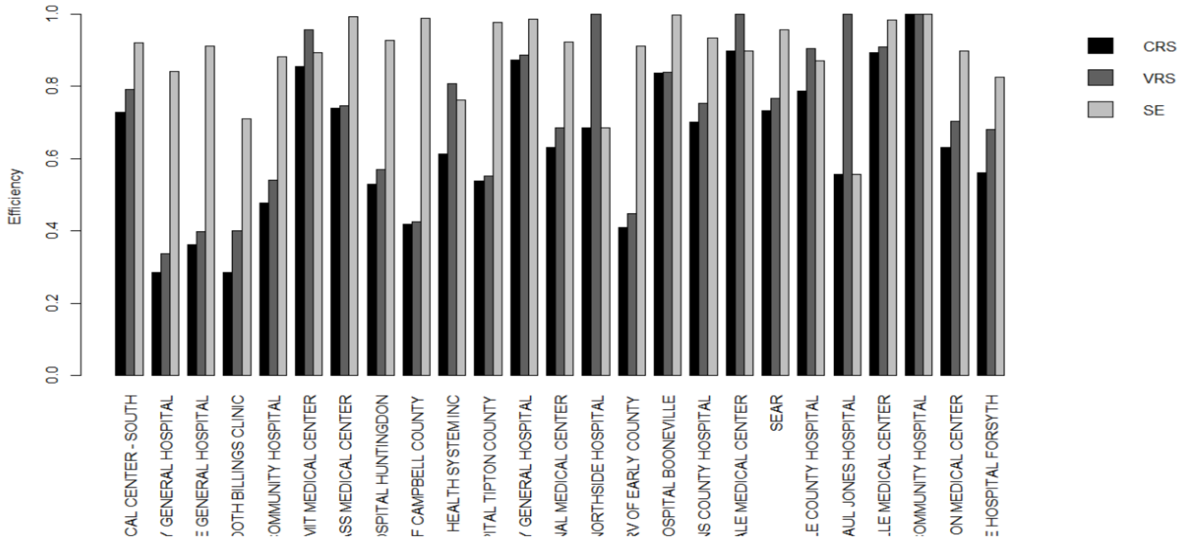

Figure 7: DEA Results for CRS, VRS, and SE model

The input-oriented approach considers a hospital to be technically efficient if the hospital can reduce its inputs (total administrative cost) while still delivering the same outcome or more (inpatient outpatient discharges, admission, bed capacity). Comparing the results of our CRS, VRS, SE we can see that our VRS results are on average better than our CRS. We can also see that 95% of our hospitals can be optimized to meet their ideal SE. That optimization is quite difficult as the optimization for one hospital will not necessarily produce the same positive effect on the entire hospital system.

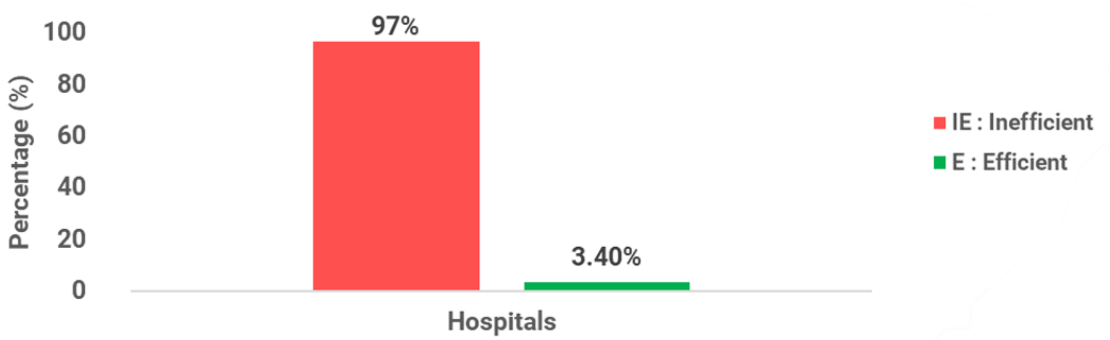

Figure 8: Percent of Efficient records in our data sets

Looking at our results, 97% [Figure 8] of our row count is inefficient while 3.4% is efficient. This result is based on the combined result of Data Envelopment Analysis and Stochastic Frontier Analysis. We used the mean Method mentioned above to generate the combined score. Since some hospitals have multiple locations, that explains why 97% of our records are inefficient while only 95% of our hospitals are inefficient.

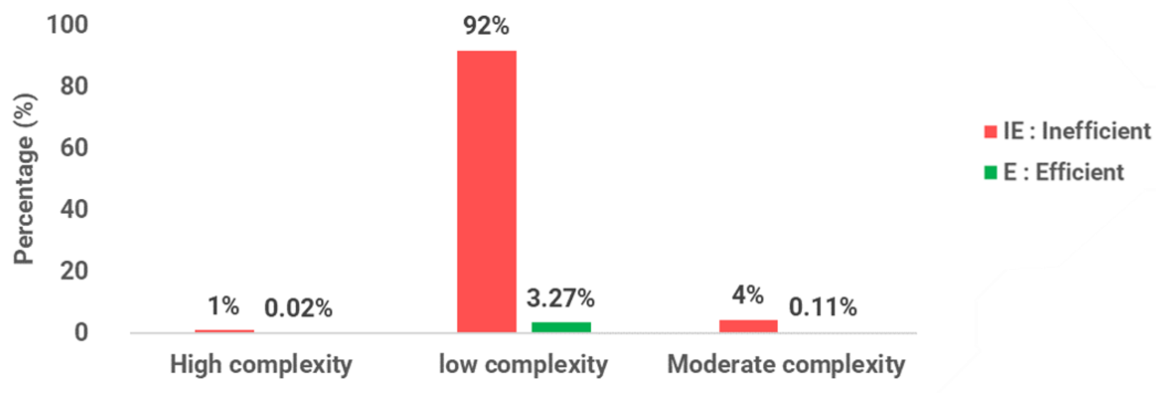

Figure 9: Percent efficient hospitals based on specialty grouping

Looking at our results with our provider specialty complexity grouping. We realized that our high complexity group which is hospitals with 6 to more specialties, and our moderate complexity group which is hospitals with 3 to 5 specialties are doing worst than our low complexity hospitals which have 1 to 2 specialties. While the percentage of efficient hospitals is low in all groups[Figure 9], we can see that the low complexity group has a better ratio compared to the other groups. Our explanation is based on how complex certain services provided by a hospital can be, and how those complex services, may require a higher input to be achieved. For example, a hospital that provides family medicine services should have a lower complexity compared to a hospital that provides surgery, rehabilitation, cancer, and cardiovascular services all at the same time. Those specialties require more equipment, requires more staff, and specifically more skilled staff. That increase in the input will not always be met with a proportional increase in outputs. Which in conclusion results in the hospital being overly inefficient.

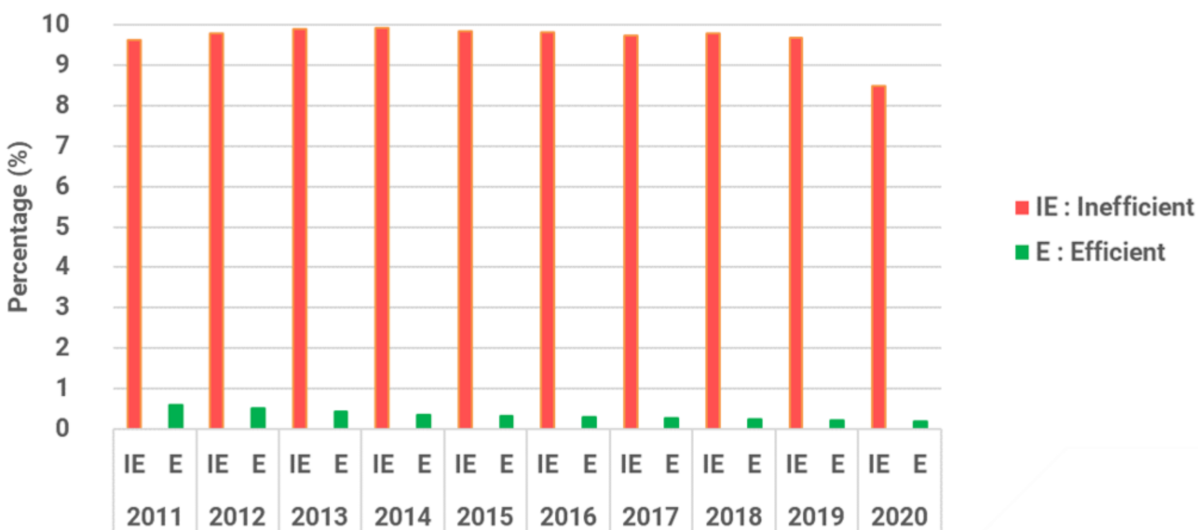

Figure 10: Annual percent of Efficient hospitals

Looking at an annual efficiency trend, we can identify 2011, and 2012 as the years when the CMS hospitals were the most efficient [Figue 10]. We can also see a decrease in hospital inefficiency in 2020 which we attribute to the direct effect of the covid 19 pandemic. During the pandemic, a lot of hospitals experience a high increase in utilization [Figure 11] in other words while their inputs were the same, the hospitals saw a big increase in their outputs which in most cases made those hospitals less inefficient since now their outputs matched their inputs. All the hospitals in our data set were affected by that fact, fortunately, since we used Sthocastic frontier Analysis, we were able to handle that effect in the data, while all hospitals experience an increase in efficiency score in 2020, SFA was able to prevent all of our hospitals in 2020 to be suddenly become efficient with an efficiency score of 1.

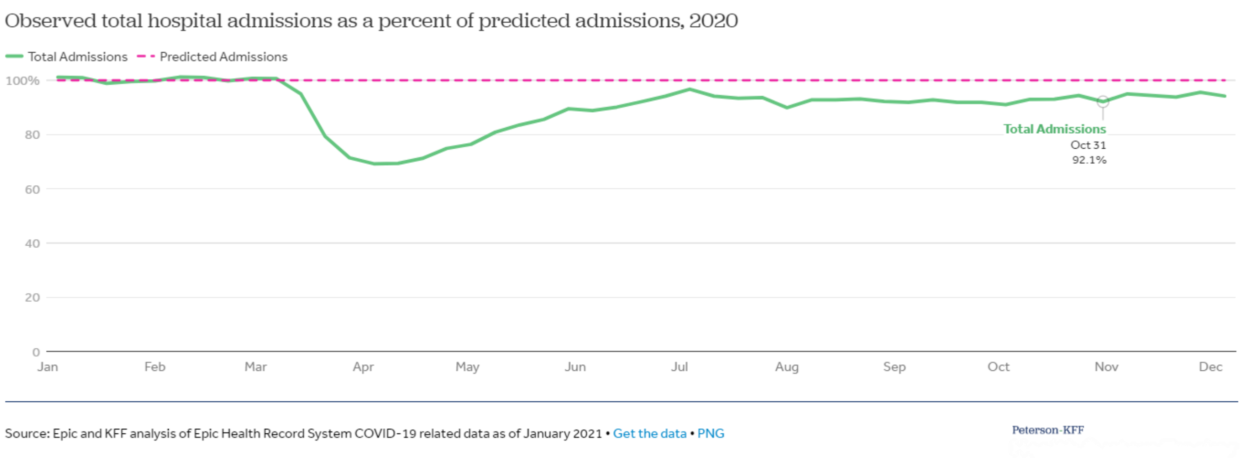

Figure 11: Hospital Utilization in 2020 increases up to 90%

On average, during our 10 years period from 2011 to 2020, we saw a decline in efficiency for the Centers for Medicare & Medicaid Services (CMS) hospitals [Figure 12]. On average the CMS hospitals had an efficiency score below 0.7 in 2011 and a decline below 0.6 by 2020. Without the increase in utilization in 2020, the efficiency decline for CMS hospitals could have been even greater.

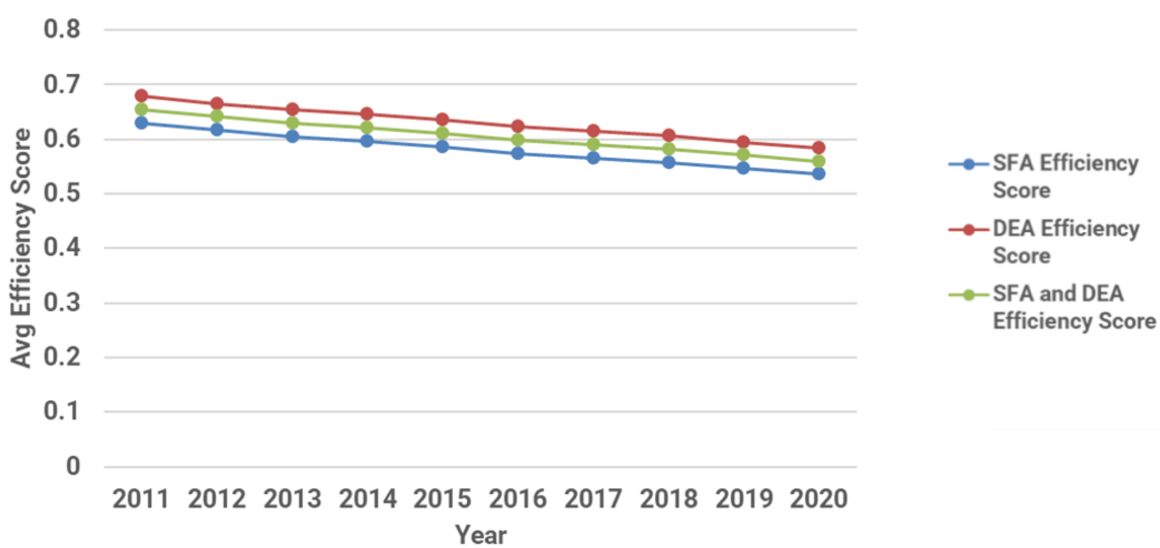

Figure 12: Annual efficiency trends

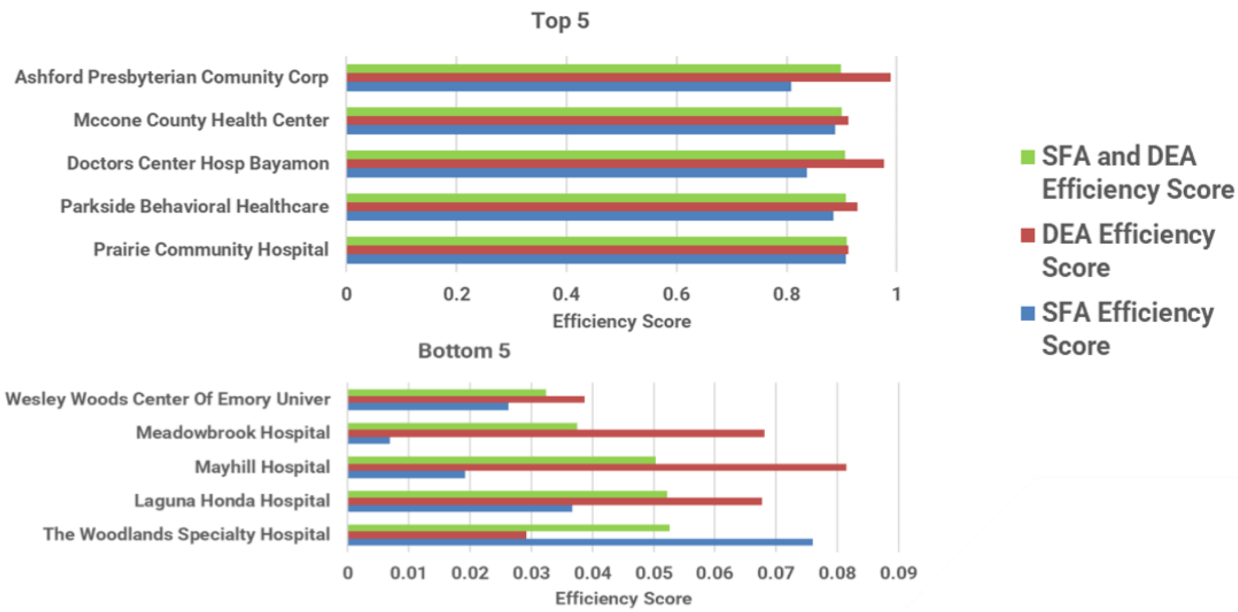

Figure 13: Top 5 efficient vs bottom 5 inefficient hospitals

Looking at the top 5 efficient hospitals of the Centers for Medicare & Medicaid Services (CMS) across the 10 years from 2011 to 2020, we can see their efficiency score is between 0.9 and 1, while the Bottom 5 or the less efficient hospitals have an efficiency score below 0.1. This shows how big of a gap in efficiency score (0.8) there exists between those hospitals. The hospitals with the worst efficiency scores can be improved greatly as there exist other hospitals in the real world with the proper policy and spending distribution that can make them efficient. Hospitals can learn from their market, they can benchmark themselves against other hospitals, and adopt new policies that can make them better. Efficiency score is not a metric that is calculated in the hospital world as it should yet it can offer them a lot of insights on spending and cost allocation.

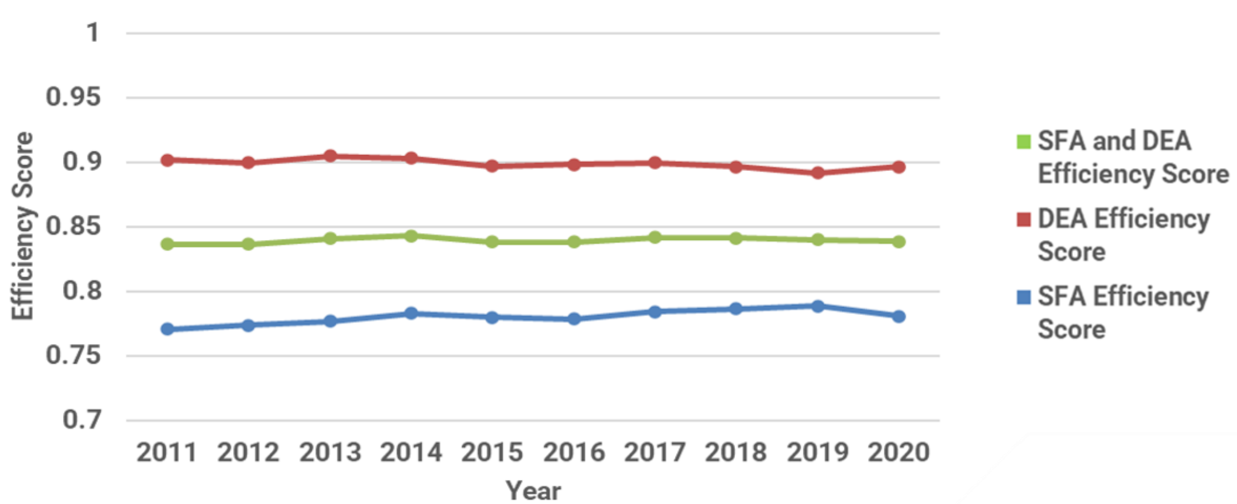

Figure 14: Top efficient hospital trends

On average top efficiency, hospitals have an efficiency score that has very low variation. In the above graph [Figure 14] you can see how consistent those hospitals' efficiency scores are throughout the 10 years. This consistency is the effect of hospital leadership having full control over hospital inputs and cost allocation. Hence with proper policies and control of inputs, hospitals can easily position themselves to be more efficient.

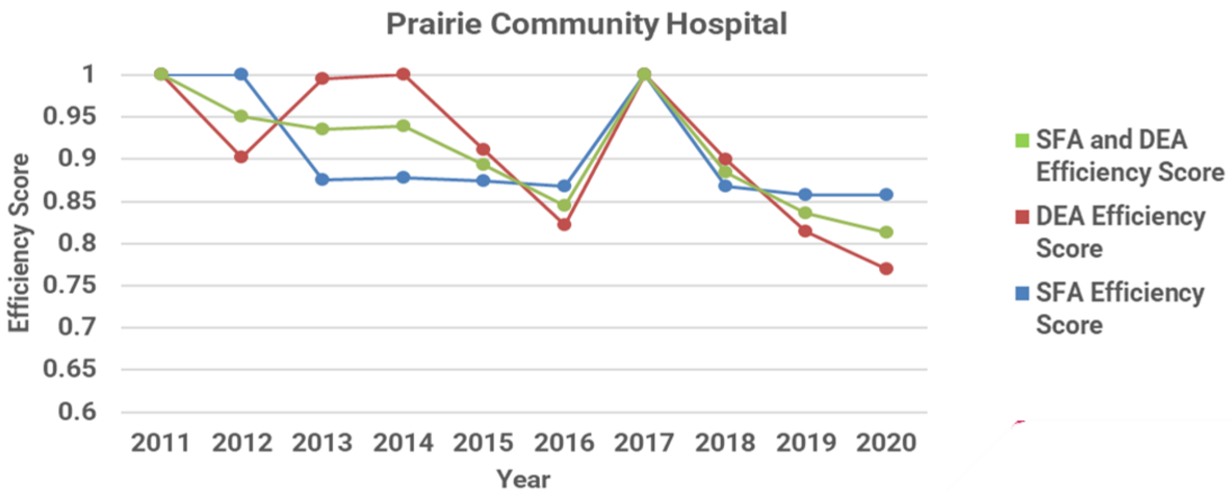

Figure 15: Top-performing hospital annual trends

As mentioned earlier, calculating efficiency can be very difficult as there are so many external factors that have a direct impact on the score. The above figure [Figure 15] shows the effect of inflation on the efficiency score of our top-performing hospitals. From 2018 to 2019 and 2020, the efficiency score of the hospital decreased by about 0.2 this is reflective of the increase in healthcare input cost due to inflation [Figure 16]. As the inflation, and labor shortage increased, hospitals spend more and more in certain areas while not being able to provide the same increase in output which result in the decline in efficiency that we saw.

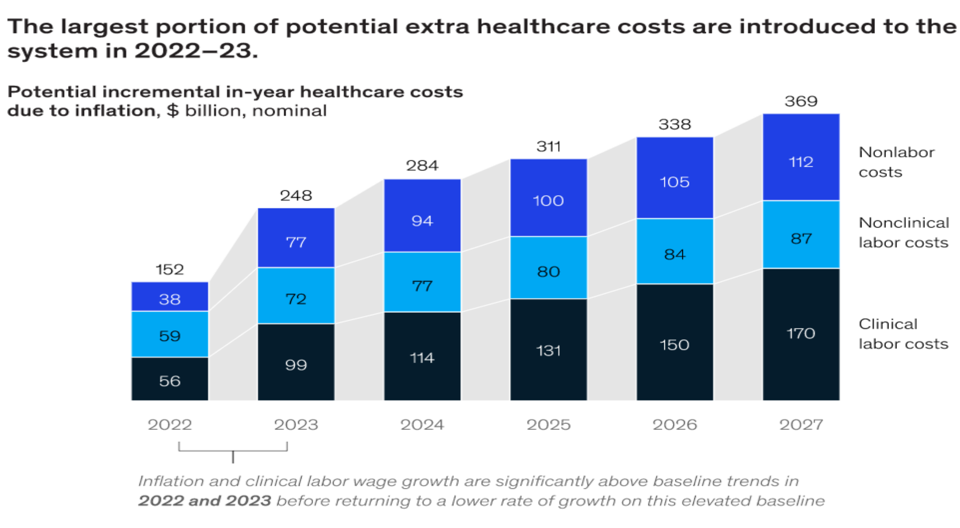

Figure 16: Increase in Healthcare input cost due to Inflation

Conclusion and Future Works

In this paper, we analyze hospital waste related to administrative cost, more specifically administrative complexity which is one of the six domains of waste. By combining Data Envelopment Analysis (DEA) and Stochastic Frontier Analysis (SFA) model results, we were able to obtain the mean average efficiency score which is the best practice to obtain a more precise efficiency score. The results show that the average efficiency score of the nonparametric model DEA is the highest, unlike the parametric SFA model, DEA did not measure statistical noise. The combination of both DEA and SFA gave us a more balanced and reliable efficiency score.

It can be concluded that during the 10 years of 2011 to 2020, 95% of the hospitals in our Centers for Medicare & Medicaid Services (CMS) data set were inefficient. The percentage of efficient hospitals is low in all of our provider specialty complexity groupings. The high complexity group which is hospitals with 6 to more specialties and the moderate complexity group which is hospitals with 3 to 5 specialties are doing worst than our low complexity hospitals which have 1 to 2 specialties. We investigate the annual efficiency trend and identify 2011, and 2012 as the years when the CMS hospitals were the most efficient [Figue 10]. We also noticed a decrease in hospital inefficiency in 2020 which we attribute to a direct effect of the covid 19 pandemic. During the pandemic, a lot of hospitals experience a high increase in utilization while their inputs remain the same. Globally, during our 10 years period we saw a decline in efficiency, in average the CMS hospitals had an efficiency score below 0.7 in 2011 and a decline below 0.6 by 2020. Comparing the top 5 efficient hospitals to the bottom 5, the less efficient hospitals have an efficiency score below 0.1 while the efficient hospitals have a score above 0.9. The gap in efficiency score (0.8) between the top 5 and bottom 5 shows there exists room for improvement for many of the hospitals in the CMS data. We investigated some of the external factors that may affect hospital efficiency some of which are inflation, and labor shortage increased. Hospitals spend more and more in a certain area while not being able to provide the same increase in output which can result in a decline in efficiency.

Our big takeaway is that hospitals regularly benchmark themselves against other hospitals in their market and use that knowledge to adjust administrative design and structure to make themselves more efficient. Knowledge sharing can also make a big difference as inefficient hospitals should be able to implement some of the policies/guidelines that have made other hospitals very efficient. You can find all data and resources used for this project on the github link below:

https://github.com/rgile002/Hospital-Cost-Efficiency-Analysis

As future work, we couldn’t tackle the simulated reduction in Hospital administrative cost and evaluate to see the impact of such reduction on the hospital output (inpatient outpatient visit/discharges, bed utilization) and bottom-line profitability. We have used CRS, VRS for DEA, and SFA with and without time effect. There are other parametric methods such as the thick frontier approach (TFA) and deterministic frontier approach (DFA) and CCR-BCC in the DEA that can be considered. We can also use an extended dataset that includes private hospitals, teaching hospitals, and research hospitals for a more complete representation of the hospital market. We can also use more member or hospital visits related data to have a deeper understanding of readmission rate, length of stay, and quality of care. We know that certain specialties may warrant an increase in hospital input while not generating the matching outputs, we can also take a deeper look and try to identify those specialties so a hospital would have a better understanding of how a specific specialty may impact their efficiency metrics. We can investigate the correlation between profits and administrative efficiency so hospitals can see the economic benefits of being efficient. Lastly, we can take a deeper look to see if more efficient hospitals are better businesses.

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