Healthcare Analytics: Strength in Numbers

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Background

- My advanced degrees are in operations research (OR)
- OR is a field which uses advanced analytical methods to help make better decisions
- I have been a member of INFORMS since 1974
- INFORMS sponsors a Conference on Business Analytics & Operations Research each Spring

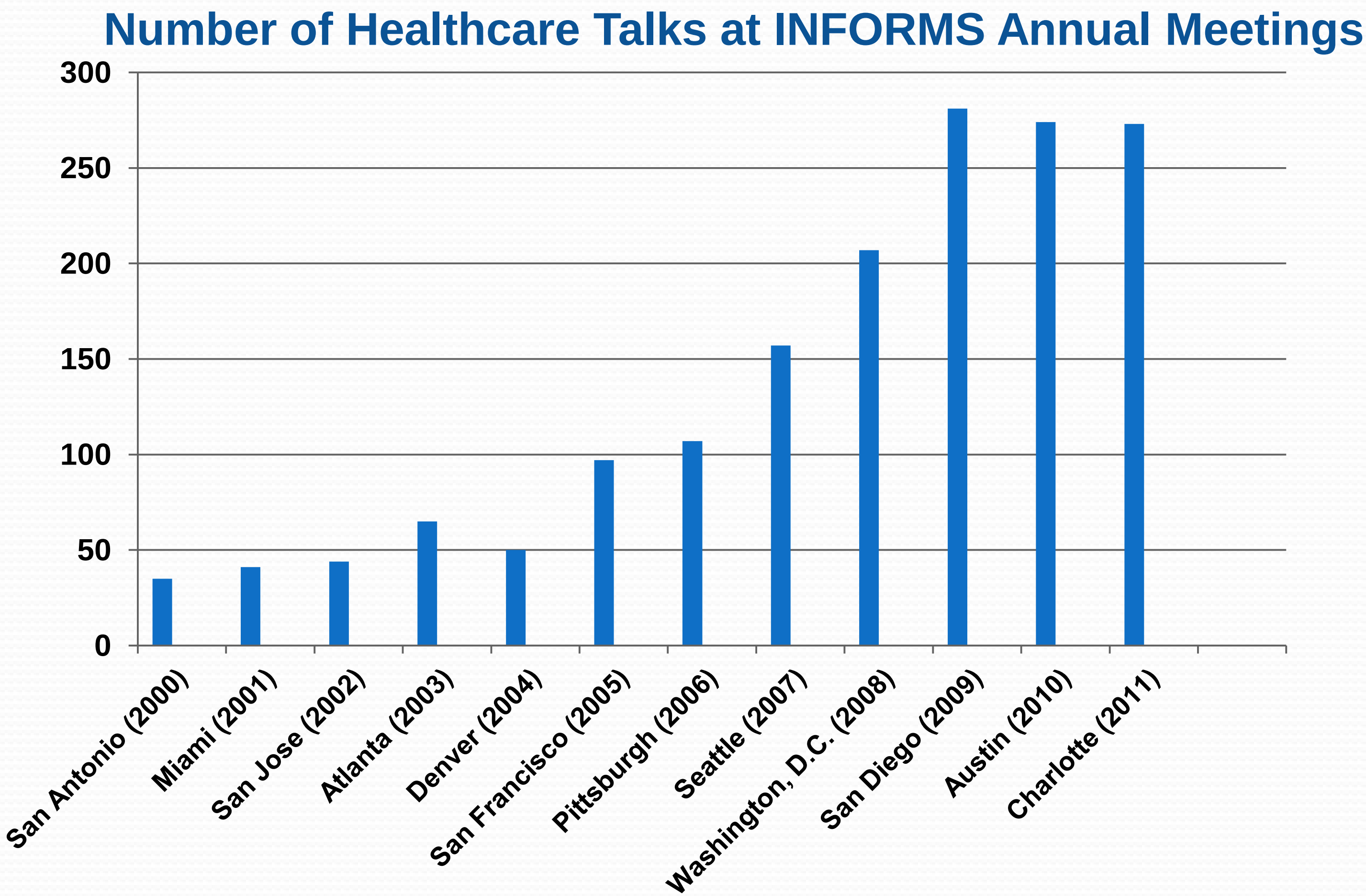
Background II

- In Moliere's play *The Bourgeois Gentleman*, Mr. Jourdain discovers that he has been speaking prose all his life, and didn't even know it!

- Well, Mike, Margrét, and I have been doing business analytics ever since we were graduate students, but we didn't use that name

- I began working on healthcare applications about six years ago

Emergence of Healthcare Analytics within INFORMS



Above numbers courtesy of Brian Denton

Strength in Numbers

- **There is more healthcare data available than ever before**
  - **Careful analysis of healthcare data can lead to smarter decisions, better quality healthcare, and cost savings**

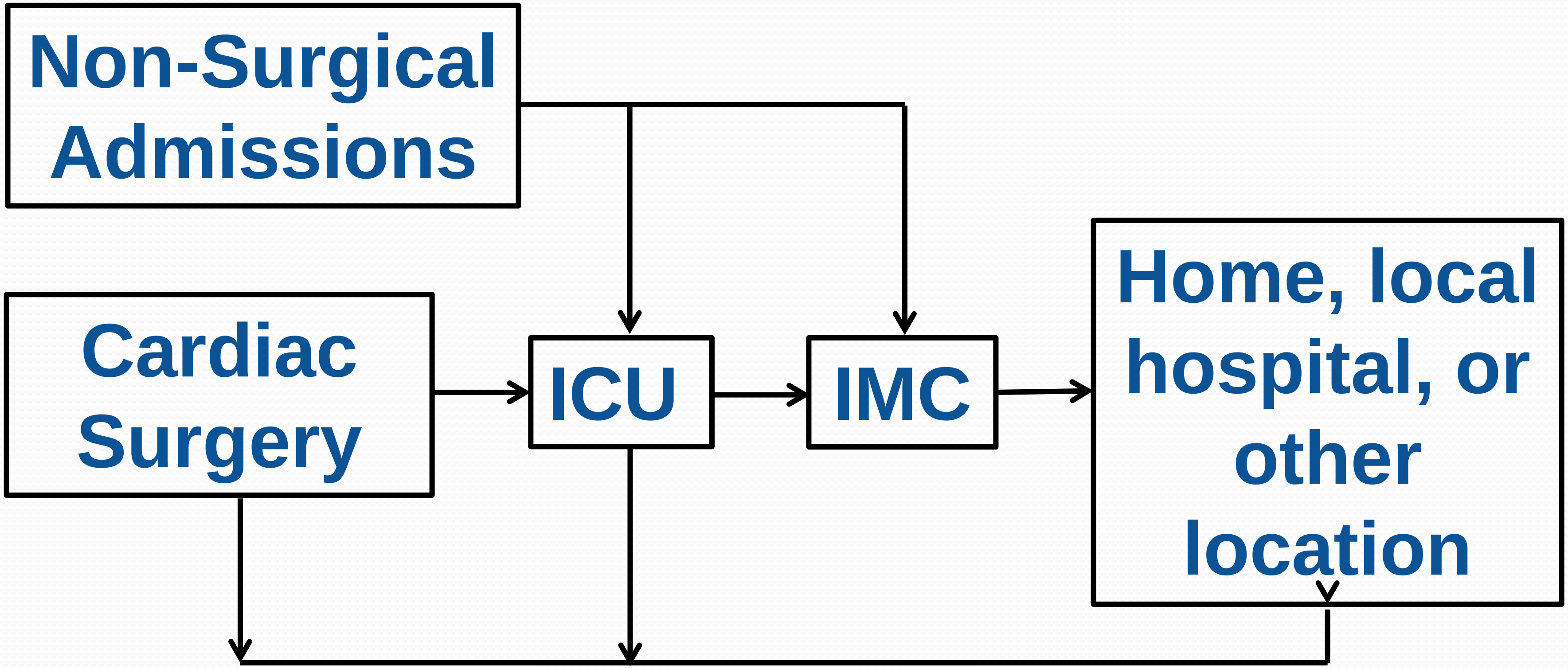
- **A larger number of healthcare decision makers have MBAs than ever before**
  - **They understand that we can help**

- **A larger number of us in OR/OM are working on healthcare applications than ever before**

Maximizing Cardiac Surgery Throughput

- **The Cardiac Surgery service line at the UMMC has 30 beds that are split between the intensive care unit (ICU) and the intermediate care unit (IMC)**
- **At the time of the study, there were 11 ICU beds and 18 IMC beds**
- **One bed was not in use because of insufficient staffing**
- **<u>Key Question</u>: What is the best mix of ICU and IMC beds?**

Flow of Patients



Note: IMC beds are less intensive and less expensive than ICU beds

Data Set

- The data set contained detailed information about the length of stay for every cardiac surgery patient for a two-year period (2005-2006)

- 1,675 patients had 1,725 operations and spent more than 17,000 days in the hospital

Methodology

- We used the data to perform a simulation of different mixes of ICU and IMC beds
- We maintained the current staffing level of 80 nurses
- Each mix of ICU and IMC beds was simulated 1,000 times for four months each time

Results

- The 14/12 bed mix enabled a total volume increase of 20%
- Each cardiac surgery provides a net income of roughly $20,000
- Staffing levels are constant, so there is no additional cost for nurses
- The 14/12 bed mix yields an annual increase in profit of $4.58 million
- This work can be reproduced in other service lines (e.g., neuro) and at other hospitals with similar results

Life is All About Timing

- There is significant variation in the quality of care from one hospital to the next

- We examine how quality varies within hospitals between daytime (6 am- 6 pm) and off-hours

  (6 pm- 6 am)

- We focus on trauma patients
  - By trauma, we mean sudden physical injury

Trauma

- Examples
  - Car crashes
  - Traumatic brain injury
  - Gunshot wounds
- Trauma is the leading cause of death among Americans ages 1 to 44 (122,000 deaths a year)
- Trauma patients are treated at a wide variety of hospitals
  - Short treatment cycle
  - Clear quality metrics

Data

- **National Trauma Data Bank created and maintained by the American College of Surgeons**
- **Data on over 1.5 million patients from 477 hospitals**
- **Detailed data: patient demographics, hospital characteristics, treatment characteristics, outcome, payment type, comorbidities, and more**

Quality Measures

- **Mortality**
- **Waiting time to surgery**
- **Length of ICU stay**
- **Surgical complication rate**
- **Number of surgeries required**

Empirical Analysis

- **Regression modeling**
- **Logistic regression modeling**
- **The findings focus on an average patient and show how outcomes change if patient arrives in daytime, night, or early am**

Modeling Outcomes

Measure	Daytime	Night	Early am
Mortality rate (L1)	0.10	0.104	0.108
Mortality rate (L2)	0.10	0.104	0.109
Mortality rate (L3-4)	0.10	0.114	0.131
Mortality rate (all)	0.10	0.111	0.111
Complication rate	0.125	0.131	0.135
Multiple surgery rate	0.786	x	0.806
Time to surgery (mins.)	182.5	175.4	167.9
ICU LOS hours	9.78	10.32	10.61

Initial Observations

- **Prompt treatment is essential in trauma care (the Golden Hour)**
- **To our surprise, longer waits for surgery did not occur during off-hours**
  - **Hospitals are not as busy at night**
  - **Operating rooms are mainly idle**
- **Still, outcomes at night/early am were clearly worse than during daytime**

Explanation of Outcomes

- Staffing levels differ between daytime and off-hours
- There tend to be generalists on duty overnight
- More resources and specialized resources are available during the daytime
- More experienced physicians prefer to work during the daytime
- Therefore, we expect a higher quality of care during the daytime and the model outcomes confirm this

Differences Between Hospitals

- The differences in resource availability between day and off-hours at small hospitals are greater than at larger hospitals
- Level I trauma centers are required to have certain surgical specialty staff available at all times
- Therefore, we expect to see larger differences in outcome between daytime and off-hours at lower level trauma centers, and smaller, more resource-constrained hospitals

Differences by Hospital Type

- Increase in mortality rate compared to daytime

	Level 1	Level 2	Level 3-4
Early am	11.0%	14.3%	30.6%
Night	10.1%	13.1%	18.9%

- Increase in surgical complication rate compared to daytime

	Level 1	Level 2	Level 3-4
Early am	9.2%	10.8%	31.9%
Night	4.6%	4.7%	8.2%

Discussion

- Patients who arrive at night or the early morning to trauma centers receive lower quality care than patients who arrive during the day

- The decrease in quality of care is largest at small, resource constrained hospitals and at lower level trauma centers

- There are fewer specialized doctors available off-hours, which leads to lower quality

- Mitigation strategies: Increase staffing levels and mimic the Dr. Cowley Shock Trauma Center

The Effects of Bed Utilization on Discharge and Readmission Rates

- Many hospital resources are required for surgery
  - Operating rooms
  - Nurses
  - Anesthesia team
  - Post-operative beds for recovery
- If downstream beds are unavailable, surgery might be postponed or cancelled
- Surgeons decide when patients are discharged
  - Surgeons are paid to do surgery

Research Question 1

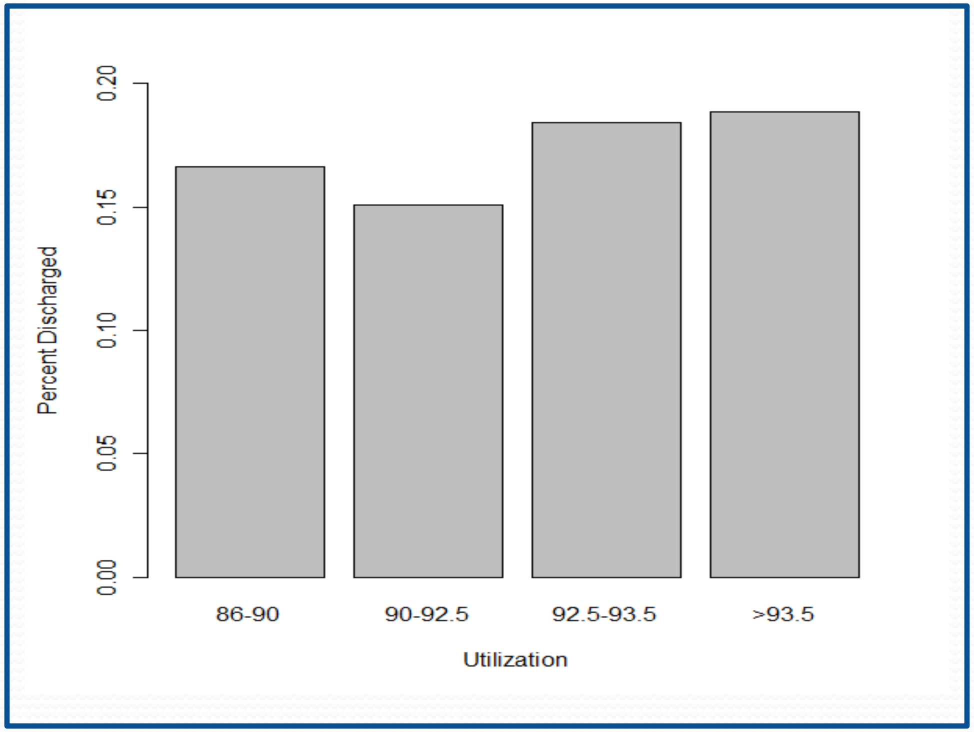
- Does the utilization of downstream beds affect the discharge decisions of surgeons?
  - Hypothesis: There is an increased discharge rate on days when post-operative utilization is high

Data

- Data collected on every surgery performed at a large US hospital from Jan 1, 2007 to May 31, 2007
- 7808 patients, of which 6470 were admitted to the hospital and stayed for at least one night
- These patients stayed a total of 35,478 days
- Data provided on age, race, gender, surgical line, date of surgery, discharge date, and surgery type (scheduled vs. emergency)
- Utilization of post-operative beds varies widely

Discharge Rates

- Discharge rates have positive correlation with utilization



Utilization Measures

- **We compute two measures of utilization**
  - **Discrete measure – a variable that is 1 when utilization exceeds a given threshold (e.g., 93%), and 0 otherwise**
  - **Continuous measure – a variable that counts the number of beds in use on each day**

- **Compare marginal effect of each bed in use vs. a discrete change in discharge probability when utilization exceeds a threshold**

Discrete Time Survival Analysis

- Can't use logistic regression because observations are correlated -- a patient discharged on the fifth day cannot be discharged on the first four days
- Singer and Willet (1993) show how to handle discrete time survival data
- For each day, we record whether or not each patient is discharged, and use this as the outcome variable
- The outcome variable is regressed on our utilization measures and our control variables
- We control for the patient's age, race, gender, severity, and surgery type

Models and Results

- **Model 1:** $logit(DISCHARGE) = AGE + ELECTIVE + FULL + CARDIAC\ SURGERY + CARDIOLOGY + \ldots + DONOR\ SERVICE + D1 + D2 + \ldots + D59 + \varepsilon$

- **Model 2:** $logit(DISCHARGE) = AGE + ELECTIVE + BEDS + CARDIAC\ SURGERY + CARDIOLOGY + \ldots + DONOR\ SERVICE + D1 + D2 + \ldots + D59 + \varepsilon$

- **When the utilization threshold is exceeded, the odds of discharge for any given patient increase. The estimate for Full is positive and significant for threshold above 91.5%.**

- **Each additional bed in use increases the odds that a patient will be discharged. The estimate for Beds is positive and significant.**

Observations

- Discharge rates increase as utilization increases, regardless of how utilization is measured
- Either some patients are held too long and discharged when space is needed, or some patients are discharged too early when utilization is high
- Our results cannot distinguish between these two explanations

Research Question 2

- **Are patients who are discharged when utilization is high more likely to be readmitted?**
  - **Hypothesis: An increase in the discharge rate will lead to some patients with shortened lengths of stay. This will cause an increase in the readmission rate for those patients.**

Analysis

- **Using the same data set, we apply logistic regression to study the effect that utilization has on the probability of readmission for a specific patient**

- **We use readmission within 72 hours as our dependent variable**

- **Hypothesized logistic regression model**

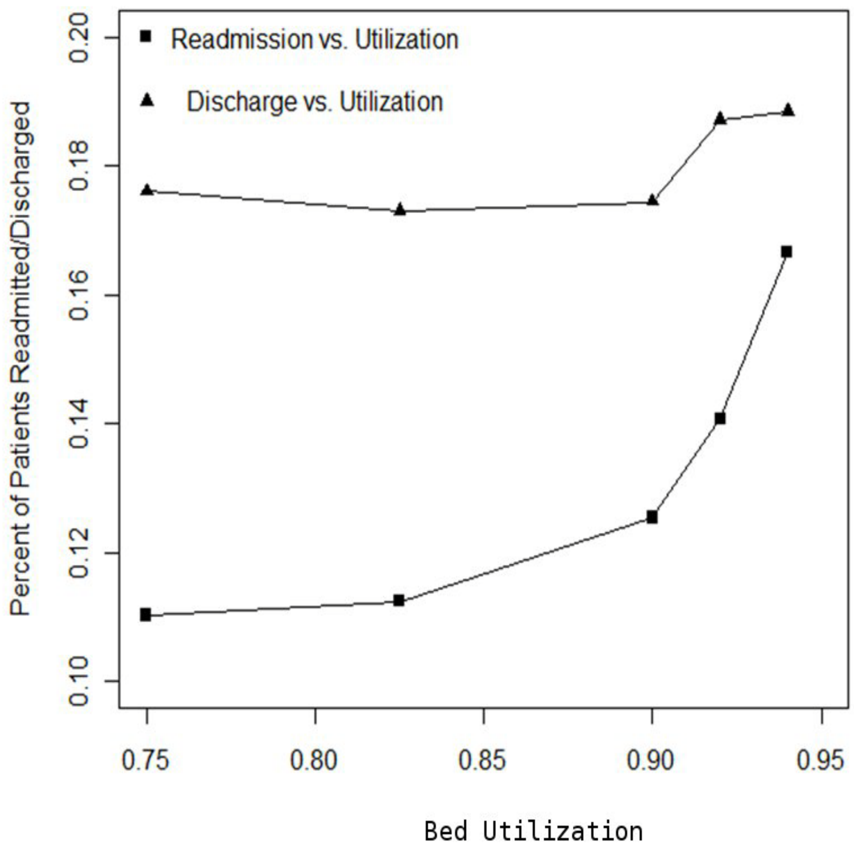
logit(READMISSION72) = AGE + BLACK + ASIAN + HISPANIC + FULL + ELECTIVE + TRANSPLANT + TRAUMA + … + NEURO + MALE + ε

Results

- **Model with Full: Controlling for race, age, gender, and the type of surgery, being discharged from a full post-operative unit increases the odds of readmission by a factor of 2.341**

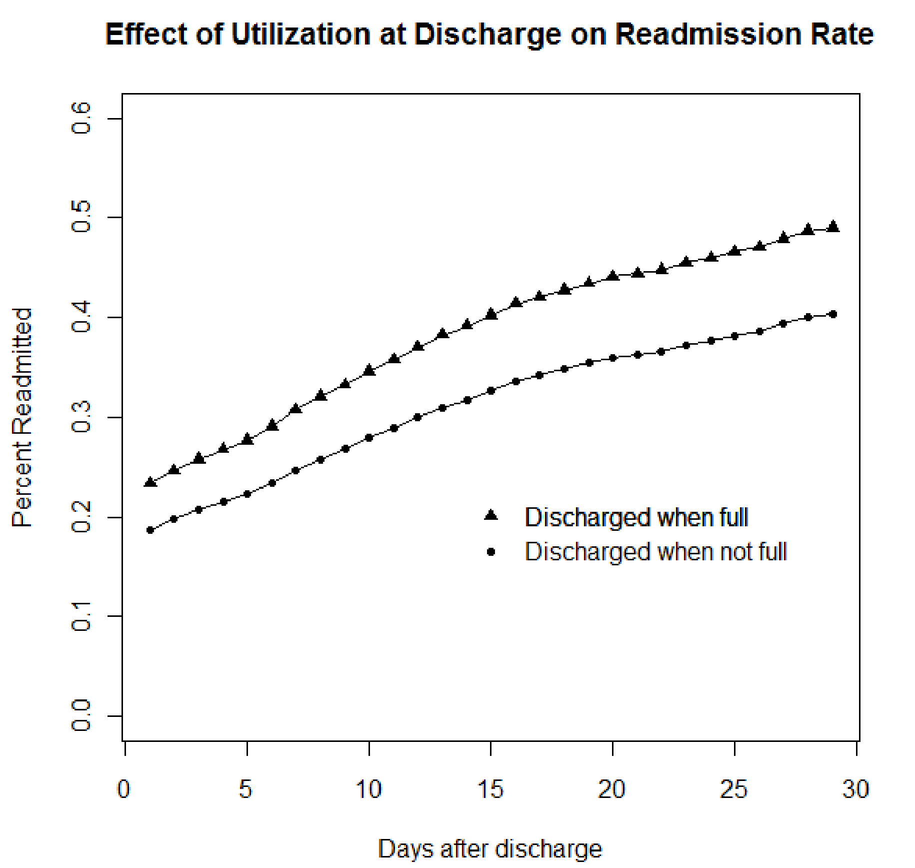
- **Model with Beds: Controlling for race, age, gender, and the type of surgery, each bed in use at the time of discharge increases the odds of readmission by a factor of 1.008**

Utilization – Readmission Relationship



The discharge rate and readmission rate both increase as utilization increases

Survival Analysis



Over the course of a month, patients discharged from a full hospital are much more likely to be readmitted

Discussion

- The discharge rate rises when utilization is high
- This corresponds to an increase in the readmission rate
- We conclude that some patients are discharged too soon when utilization is high
- Surgeons have an incentive to clear space for their surgeries
- Mitigation strategy: Use a checklist before discharging a patient—force the surgeon to think about whether the discharge is for the right reason

Conclusions

- Our research team is working with hospitals in Baltimore and Washington, D.C.
- There are more opportunities to apply healthcare analytics than we can handle
- Our colleagues at other universities are in the same situation
- The future of healthcare analytics looks very bright