Workshop on Healthcare Operations
8-10 September 2018
Bath UK

Master Class 3
Empirical Modelling in Healthcare

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(and Assistant Professor Jillian Jaeker)

Agenda

- Overview of some of my empirical research projects
- Quick mention of some empirical methods in healthcare operations research
- Getting your research published

6 Different Projects Using Empirical methods

Anita L. Tucker
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healthcare operations management
operational failures
internal supply chains
lean
process improvement

GET MY OWN PROFILE

	All	Since 2013
Citations	2859	1609
h-index	17	18
i10-index	20	19

DE at JOM
AE at Man Sci
AE at M&SOM
Former AE at POM

TITLE	CITED BY	YEAR	
Why hospitals don't learn from failures: Organizational and psychological dynamics that inhibit system change AL Tucker, AC Edmondson California management review 45 (2), 55-72, 2003	805	2003	Ethnography, Interviews, Survey of nurses
The diseconomies of queue pooling: An empirical investigation of emergency department length of stay H Song, AL Tucker, KL Murrell Management Science 61 (12), 3032-3053, 2015	79	2015	Diff-in-Diff (Kaiser P.)
Past the point of speeding up: The negative effects of workload saturation on efficiency and patient severity JA Berry Jaeker, AL Tucker Management Science 63 (4), 1042-1062	51	2016	Spline (State of CA data)
The value of process friction: An empirical investigation of justification to reduce medical costs J Berry Jaeker, A Tucker	1	2017	Logistic Regression (Rhode Island)
Capacity Pooling in Hospitals: The Hidden Consequences of Off-Service Placement H Song, A Tucker, R Graue, S Moravick, J Yang		2018	Instrumental Variables (BIDMC)
The impact of workaround difficulty on frontline employees' response to operational failures: A laboratory experiment on medication administration AL Tucker Management Science 62 (4), 1124-1144	16	2015	Experiments (Nursing conventions

Why Use Empirical Methods?

Picture Source: Mckinsey.com

Pre-Knowledge about issue

4. Test Effectiveness of Solution
3. Quantify Effects
2. Test theory
1. Observe Phenomenon

Purpose

Different Types of Empirical Methods

Pre-Knowledge about issue

4. Experiments
3. (Secondary) Data Analysis
2. Survey Research
1. Ethnographic studies

- Overview of some of my empirical research projects
- Quick mention of some empirical methods in healthcare operations research
- Getting your research published

1. Ethnography

- Gather data embedded in context
  - Observations, interviews, artifacts
- Deepen understanding of context
- Need for rigor in methods used
  - Collecting, analyzing and presenting data

Example of Data Collection

TABLE I. An Overview of Hospitals where Observation of Workers Occurred

Hospital	Type of Hospital	Number of Beds	Nursing Units Observed	Unionized Nurses	Observation Time (hours:min)	% of Total Observation Hours	# of Nurses Interviewed
1	Small Community	47	Intensive Care Unit	Non-Union	82:35	34%	0
2	Specialty, Urban, Teaching	98	Surgical	Non-Union	7:45	3%	0
3	Rural Community	134	Medical/ Surgical	Union	27:19	11%	2
4	Community, Private Not-For-Profit	243	Surgical and Maternity	Non-Union	34:30	14%	1
5	Community, Government	292	Oncology & Medical/ Surgical	Union	15:35	7%	3
6	Community, Government	250	Cardiac	Union	1:30	1%	1
7	Teaching, Urban	198	Oncology	Non-Union	20:30	9%	2
8	Pediatric, Teaching, Urban	163	Oncology	Union	9:11	4%	1
9	Teaching, Tertiary Care	433	Intensive Care Unit	Non-Union	40:30	17%	2
Total					**239:25**		**12**

A.L. Tucker, Edmondson, A.C. 2003. Why hospitals don't learn from failures: Organizational and psychological dynamics that inhibit system change. *California Management Review.* **45**(2) 1-18.

Example of Deepen Understanding

The new mother, seated in a wheelchair and cradling her two-day-old infant in her arms, was ready to leave the hospital when Abby, the nurse on duty, noticed that the security tag that should encircle the baby's ankle was missing. These reusable tags were expensive, costing over $100 each. Abby quickly searched for the tag and was able to locate it in the baby's bassinet. Three hours later, a similar event occurred. This time, despite enlisting assistance from other nurses and spending eight minutes looking in the bassinet and the nursery, Abby was unable to find the tag and notified the nurse manager of its disappearance. It seemed likely that the distracting and potentially serious problem would happen again because investigation into underlying causes of the two incidences had not occurred.

The first author, observing both events, was struck not only by this seemingly unusual problem's recurrence but also by Abby's and the nurse manager's lack of attention to seeking root causes for this annoyance. This inattention was surprising for two reasons. First, the nurse commented that the security tags had fallen off both of the babies she discharged that day, implying that she understood the significant and recurring nature of the problem. Second, the security tag system was less than a month old, which means that managers and nurses should have had a heightened sensitivity to the system's shortcomings and have been more motivated to resolve breakdowns in the new technology (Tyre and Orlikowski, 1994). It is exactly

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A.L. Tucker, Edmondson, A.C., Spear, S. 2002. When problem solving prevents organizational learning. *Journal of Organizational Change Management.* **15**(2) 122-137.

What I mean by rigor

Results

In 197 hours of observation of 22 nurses, we documented 120 problems (or, approximately one every 1.6 hours of observation). Examples include the following (in descending order of cumulative time spent):

(1) missing or incorrect information;
(2) missing or broken equipment;
(3) waiting for a resource; and
(4) missing or incorrect medication.

To compute interrater reliability, a random sample of ten observation days was evaluated independently by two non-nurse reviewers. The kappa statistic, which adjusts the rating downward to compensate for the probability that raters could assign items to the same category by chance, was appropriate to use in this situation. The kappa value was 0.88 for judgments about problem type, which is considered almost perfect by Landis and Koch (1977).

Table 4
Summary statistics for operational failure impact measures ($N = 194$)

Measure	Mean	Standard deviation (S.D.)	Max
1. Number of additional tasks	2.0	2.3	12
2. Direct time spent on problem (min)	4.2	5.2	33
3. Indirect time (min)	0.8	3.9	39
4. Number of interruptions	0.5	0.9	6
Weight of interrupted task	1.1	1.4	
Weighted interruptions	1.3	2.1	12
5. Direct Delay until system is restored so that task can be completed (min)	24	58	365
Weight for task that was delayed	2.3	1.6	4
Weighted Direct Delay	81	209	1440
6 Indirect Delay AFTER system is restored (min)	7.8	37	300
Weighted indirect delay until task completion	28	141	1200
7. Risk to patient	1	1	3
8. Number of people involved in resolving problem	1.2	1.1	8
9. Waste—unnecessary procedures and tasks performed	0.3	0.8	3

A.L. Tucker. 2004. The impact of operational failures on hospital nurses and their patients. *Journal of Operations Management.* **22**(2) 151-169.

2. Data Analysis

- Continuous Outcome Variable
  - Ordinary Least Squares (OLS) Regression (Song et al., 2015)
    - Fixed effects, robust, and clustered standard errors
- Models for Binary or Count Outcomes
  - Logistic regression (Berry Jaeker and Tucker, 2017)
- Inconsistent Relationship between Y and X variables
  - Splines (Berry Jaeker and Tucker, 2016
  - Mediation Analysis (Berry Jaeker and Tucker 2017)
- Endogeneity Concerns
  - Difference-in-differences (Song et al. 2015)
  - Instrumental Variables (Song et al. 2018)

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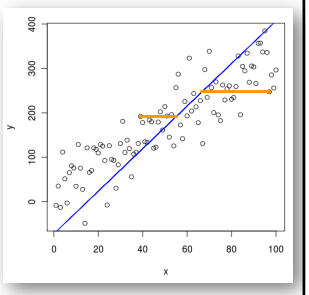
OLS Regression

- Linear regression; the "workhorse" of econometric models
- Minimizes the squares of the errors with a linear equation
- Includes:
  - An outcome variable, ***y***
  - Intercept, $\boldsymbol{\beta_0}$
  - Explanatory and control variables, $\boldsymbol{x_i}$, effect size given by $\boldsymbol{\beta_i}$
  - Error term (includes unobservable and omitted variables), $\boldsymbol{\varepsilon}$
- Error term must have mean=0 and be uncorrelated with ***x's***



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OLS

$$\ln(LOS) \quad = \beta_0 \; + \; \beta_1 \mathbf{X} \; + \; \beta_2 MD\ PRior\ PTs \; + \; \varepsilon$$

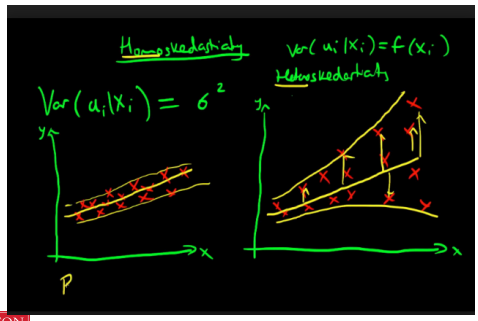
Outcome variable Log transformed to be normally distributed

Control variables with **X** being a vector of Controls, e.g., sex, age Month, year

Variable of interest

- If variable of interest is ***cumulative experience*** (e.g., number of patients treated by a physician prior to patient *i)* becomes a **learning curve** model
- Generally robust to model specifications (assuming no endogeneity), but can be made more so with
  - Robust standard errors that control for heteroskedacity
  - Clustered standard errors if there are observations that are likely to be correlated (e.g., all students in a classroom) – often used with fixed effects

Just in case you wonder what is heteroskedasticity



Logistic Regression

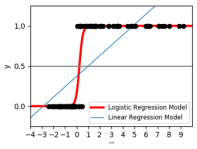
$$y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots e$$

- But, if dependent variable can only be a >0 or <1
  - Linear regression would predict values outside of this range
  - Instead, we need to use a sigmoid function to force predicted values of y to fall between 0 and 1

$$P(y) = \frac{1}{1 + e^{-y}}$$

  - Then solving for "y" gives us

$$\underbrace{\ln\left(\frac{p(y)}{1 - p(y)}\right)}_{\text{Log Odds, also called "logit"}} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots e$$



Logistic Regression

$$\ln\left(\frac{p(ultrasound)}{1 - p(ultrasound)}\right) = \beta_0 \; + \; \beta_1 \mathbf{X} \; + \; \beta_2 Justification + \cdots \; + \; \varepsilon$$

Outcome variable
1 if ultrasound; 0 if not

Coefficient is the "log odds", but is easier to interpret if you exponentiate the coefficient (e^{B2}) to get the impact on the "odds ratio" of increasing independent variable of interest by 1 unit

J. Berry Jaeker, Tucker, A.L. 2017. *The value of process friction: An empirical investigation of justification to reduce medical costs.*

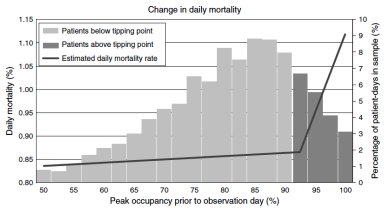
Survival Analysis

- Probability that a person will "fail" (e.g., be discharged, readmitted, die) given that they have "survived" up until that point; end point is usually censored
- Based on a hazard function, and allow variables to change over time
- Often used in public policy (e.g., long term medical studies on survival), as well as LOS in hospitals
- Continuous and discrete with parametric and non-parametric time functions
- Survival Analysis in Medical Papers
  - Kuntz et al. 2015 (Continuous w/spline, use Maximum Likelihood to estimate spline locations)
  - Berry Jaeker and Tucker, 2016 (Discrete w/spline)

Excellent Resource: https://www.iser.essex.ac.uk/resources/survival-analysis-with-stata

A Tipping Point Model

Figure 2 **The Tipping Point Phenomenon**



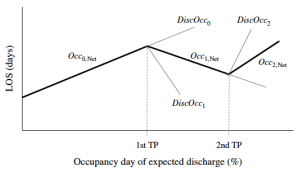
L. Kuntz, Mennicken, R., Scholtes, S. 2015. Stress on the Ward: Evidence of Safety Tipping Points in Hospitals. *Management Science*. **61**(4) 754-771.

Spline Model

We estimate the impact of occupancy on the day of expected discharge as the sum of the impact of the three different occupancies that represent our spline function with two knots:

$$\Phi OCC_i = \varphi_1 OccAdmit_i + \varphi_2 OccAdmit_i^2 + \sum_m \phi_{i,m} OccDisc_{i,m}, \quad (2)$$

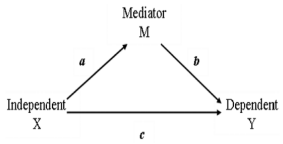
Figure 5. Diagram of the Change in LOS Before and After Tipping Points (TP) 1 and 2



J. Berry Jaeker, Tucker, A.L. 2016. Past the point of speeding up: The negative effects of workload saturation on efficiency and quality. *Management Science*. **63**(4) 1042-1062.

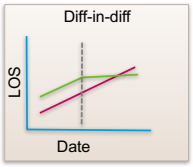
Mediation

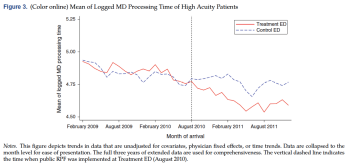
- Updated Methods
  - K.J. Preacher, Hayes, A.F. 2004. SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior Research Methods, Instruments, & Computers*. **36**(4) 717-731.
  - X. Zhao, Lynch, J., John G., Chen, Q. 2010. Reconsidering Baron and Kenny: Myths and Truths about Mediation Analysis. *Journal of Consumer Research*. **37**(2) 197-206.



Difference-in-Differences

- Include a control organization(s) to account endogeneity concern
  - Effect of time on the efficacy of a treatment





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H. Song, Tucker, A.L., Murrell, K.L., Vinson, D.R. 2018. Closing the Productivity Gap: Improving Worker Productivity Through Public Relative Performance Feedback and Validation of Best Practices. *Management Science*. **64**(6) 2628-2649.

Instrumental Variables

- Used to address endogeneity concern
  - A missing variable impacts both the independent and dependent variable
- Approach: Predict the independent variable with another variable(s) correlated with the independent variable, but not the dependent variable. Use the predicted values in your regression

$$OffService_i = \alpha + \gamma \cdot ServiceBusy_i + \delta \cdot SHBusyRatio_i + \mathbf{X}_i + \epsilon_i$$

$$Y_i = \alpha + \beta_{IV} \cdot \widehat{OffService}_i + \mathbf{X}_i + \epsilon_i$$

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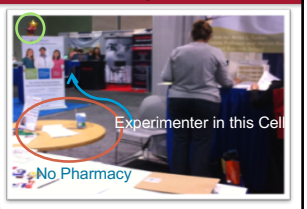
Capacity Pooling in Hospitals: The Hidden Consequences of Off-Service Placement
H Song, A Tucker, R Graue, S Moravick, J Yang 2018

Difficult & High Access Condition 4

3. Experiments

Lab or Field
I did a lab experiment
- Impact of Difficulty in working around a problem on the likelihood of suggesting improvement ideas



Easy & Low Access Condition 1

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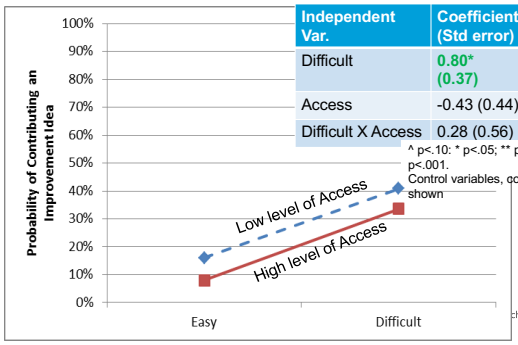
Contribute Improvement Ideas (n=137)

CONCLUSION: Difficulty of working around has a large, positive effect on the contribution of improvement ideas about operational failures



Independent Var.	Coefficient (Std error)	% Increase
Difficult	0.80* (0.37)	21%
Access	-0.43 (0.44)	-11%
Difficult X Access	0.28 (0.56)	8%

^ p<.10: * p<.05; ** p<.01; *** p<.001.
Control variables, constants not shown

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- Overview of some of my empirical research projects
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- Getting your research published

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Editorial Statement Management Science - Healthcare Management Department (DE: Stefan Scholtes)

The department invites submissions that advance knowledge of how to better organize and manage the delivery of healthcare services in developed, emerging or developing economies. Papers will offer (2) rigorously evaluated insights that are of (3) significant practical relevance for healthcare leaders (senior managers, clinicians, policy makers).

Papers should be context-specific and problem-oriented, focusing on (1) significant challenges of healthcare management, including improving patient access, improving outcomes and patient experience, reducing costs, reducing errors, managing demand, optimizing patient flow, measuring and improving population health, optimizing public health programs, leveraging technology, engaging the workforce, developing new business models, improving alignment and coordination between organizations, or improving organizational learning and innovation capabilities.

The department encourages submissions that engage with current industry trends and their managerial challenges, such as the digitization of patient records, genomics and precision medicine, value-based healthcare, integrated care, patient empowerment, behavior and choice.

Papers may draw on theory across disciplines, as appropriate for the problem addressed, and use statistical, modelling or experimental methodologies. The department particularly welcomes papers that exploit large, granular datasets and leverage the emerging field of data analytics. Criteria for publication are (i) the paper's potential for practical impact, (ii) the strength of its analysis and evidence, (iii) the originality of its main insight. The department prefers short and focused papers. The submission cover letter must include a brief non-technical executive summary for senior healthcare leaders, explaining the paper's main insight and its practical implication (max 200 words).

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1. Significant Challenge facing Healthcare Management

- **Off-Service Placement of Patients Due to High Occupancy**
  - *Study done in collaboration with the Medicine Department Leadership at Beth Israel Deaconess Hospital in Boston, MA*
- **Hospitals face capacity pressures** (Best et al. 2015; Kuntz et al. 2015)
- **Exacerbated by variability in patient demand and fixed supply of hospital beds, at both hospital and service levels** (McManus et al. 2003)
- **Periods of time when there's limited available space for new patients** (Green 2002)
- **Patients are placed in any available bed, even if its "off service"** (Armony et al. 2015; Bai et al. 2018; Best et al. 2015; Dai and Shi 2017; McManus et al. 2003; Shi et al. 2013; Stretch et al. 2017; Xie et al. 2014)

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2. Rigorously Evaluated Data Sources (Oct 1, 2015 - Sep 30, 2016)

- **Encounter** (patient-visit level), *N* = 52,630
  - LOS, patient characteristics, DRG, disposition, readmission, etc.
- **Census** (bed-day level), *N* = 240,763
  - Service, on-service v. off-service indicator
- **Capacity dashboard** (bed-hour level), *N* = 6,276,607
  - Bed status (open, occupied, reserved, closed)
- **Transfer** (patient-transfer level), *N* = 157,807
  - Transfer time, bed ID, length of stay in bed
- **Triggers** (clinical trigger event level), *N* = 5,088
  - Clinical trigger events include heart rate <40 or >130, respiratory rate <8 or >30, SaO2 <90% in spite of oxygen, acute change in conscious state, etc.
- **Patient satisfaction** (patient-visit level), *N* = 4,025
  - HCAHPS survey measures

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Instrumental Variable Approach

- **Relevance condition**
  - $ServiceBusy_i$ and $SHBusyRatio_i$ are each associated with $OffService_i$ at the 0.1% level.
  - Off-service placement more likely when service is busy (46% increase in likelihood) and when service is more congested than hospital (p < 0.01).
- **Exogeneity condition**
  - Pre-admission measures of utilization **(Kim et al. 2015)**
  - Unit-level utilization during hospitalization separately accounted for **(Kim et al. 2015, Stretch et al. 2017)**

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(3) Practical Relevance (What will managers do differently as a result?)

VARIABLES	(1) Logged Remaining Hospital LOS	(2) Logged Remaining Hospital LOS
Predicted off-service placement	0.253**	0.237**
	(0.077)	(0.077)
Predicted off-service placement x Nursing mismatch	0.011	
	(0.054)	
Predicted off-service placement x Distance		0.000065*
		(0.00003)
Unit-level utilization	10.388***	10.341***
	(1.385)	(1.398)
(Unit-level utilization)^2	-6.110***	-6.068***
	(0.826)	(0.833)
Month FE	Yes	Yes
Observations	23,077	23,077

Notes. Controls not shown include age, sex, DRG cost weight, complications or comorbidities, number of transfers, unit-level utilization and its squared term, and admission time of day. ***p<0.001, **p<0.01, *p<0.05

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Challenges & Suggestions

- Getting data can take a long time
- BIDMC took 2 years just to settle on the research topic, then another year to get the dataset!
- Don't rush to ask the hospital "Will you give me data?"
  - Answer can be "NO" if you ask too quickly, "YES" after they trust you
- Hospitals increasingly want the researcher to pay for the time required to extract the data from the EHR (~$1.5K)
- Helpful to have a physician partner. They understand and appreciate the value of research. Will want to be a co-author.
- Can help to get a research grant to pay for physician's time. (I have not yet done this)
- Get something unique: Because of EHR and public datasets, there seem to be a lot of papers on same topic, can be challenging to convince review team that your paper makes a contribution beyond what has already been published

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Challenges & Suggestions

- Writing up your results
- Start with (appropriate) most simple, most straightforward story and analysis
  - Often times this is OLS
  - Make sure you include descriptive statistics and be critical of them yourself (any red flags? Anything unusual or unexpected?)
  - Interpret the effects of your significant results in the body of the paper ("A x% increase in the independent variable is associated with a z% increase in the dependent variable")
- Anticipate objections and include robustness checks to convince reader that your results will hold
- Explicitly address endogeneity concerns from the beginning
- Answer the question in the discussion section: What would a manager do differently as a result of your study?

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Thank you!

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