Computational Health Economics & Outcomes Research

October 23, 2018

Sherri Rose, Ph.D.

Associate Professor
Department of Health Care Policy
Harvard Medical School

Co-Director
Health Policy Data Science Lab

drsherrirrose.com
@sherrirose
Of note, I do not augment my statistical model with additional causal assumptions (Pearl 2009). These assumptions are likely violated in this setting, particularly the randomization assumption (i.e., no unmeasured confounding). There are many variables that are not collected or available in the claims records used for risk adjustment, some with a plausibly confounding relationship between the medical conditions and health spending, such as socioeconomic status or education. However, I am specifically interested in informing policy and a statistical estimation question targeting the individual medical con-
Functional Causal Mediation Analysis With an Application to Brain Connectivity

Martin A. Lindquist
Using deep learning and Google Street View to estimate the demographic makeup of neighborhoods across the United States

Timnit Gebru\textsuperscript{a,1}, Jonathan Krause\textsuperscript{a}, Yilun Wang\textsuperscript{a}, Duyun Chen\textsuperscript{a}, Jia Deng\textsuperscript{b}, Erez Lieberman Aiden\textsuperscript{c,d,e}, and Li Fei-Fei\textsuperscript{a}
Double Robust Estimation for Multiple Unordered Treatments and Clustered Observations: Evaluating Drug-Eluting Coronary Artery Stents

Sherri Rose\textsuperscript{1,*} and Sharon-Lise Normand\textsuperscript{1,2}
HEALTH ECONOMICS POLICY OUTCOMES
Can Your Hip Replacement Kill You?

By JEANNE LENZER  JAN 13, 2016
Can Your Hip Replacement Kill You?

By JEANNE LENZER  JAN. 13, 2018

Why Medical Devices Aren't Safer

By AUSTIN FRAKT  APRIL 18, 2016

Things sometimes go wrong with airbags, food and drugs, prompting recalls. It can also happen with medical devices, though you’d think lifesaving devices like heart defibrillators or artificial hips would be closely monitored.

But the data needed to systematically and rapidly identify dangerous medical devices are not routinely collected in the United States.
Can Your Hip Replacement Kill You?

By JEANNE LENZER  JAN 13, 2016

Your medical implant could kill you

By Jeannine Lenzer  December 16, 2017  12:08pm  Updated

---

Why Medical Devices Aren't Safer

By Austin Frakt  April 18, 2016

Things sometimes go wrong with airbags, food and drugs, prompting recalls. It can also happen with medical devices, though you'd think lifesaving devices like heart defibrillators or artificial hips would be closely monitored.

But the data needed to systematically and rapidly identify dangerous medical devices are not routinely collected in the United States.
Can Your Hip Replacement Kill You?

By JEANNE LENZER  JAN 13, 2018

Your medical implant could kill you

By Jeanne Lenzer  December 16, 2017  12:08pm  Updated

Why Medical Devices Aren’t Safer

Austin Frakt  THE NEW HEALTH CARE  APRIL 14, 2016

Things sometimes go wrong with airbags, food and drugs, prompting recalls. It can also happen with medical devices, though you’d think lifesaving devices like heart defibrillators or artificial hips would be closely monitored.

But the data needed to systematically and rapidly identify dangerous medical devices are not routinely collected in the United States.

Are Implanted Medical Devices Creating A ’Danger Within Us’?

Dave Davies  January 17, 2018  3:10 PM ET

Medical journalist Jeanne Lenzer warns that implanted medical devices are approved with far less scrutiny and testing than drugs. As a result, she says, some have caused harm and even death.
Medical Devices

- National medical device system has been proposed
- Information to distinguish devices not currently routinely collected, nor available in medical claims (as it is for prescription drugs)
Medical Devices

- National medical device system has been proposed
- Information to distinguish devices not currently routinely collected, nor available in medical claims (as it is for prescription drugs)

Implantable medical devices represent high-risk treatments often evaluated in the premarket setting on the basis of smaller trials, are likely to change quickly over time, and have led to serious side effects.
Cardiac Stents

Expected Probability of Safety Event vs Stents
Cardiac Stents: Statistical Challenges

- Often dozens, hundreds, or even thousands of potential variables
Cardiac Stents: Statistical Challenges

- Often dozens, hundreds, or even thousands of potential variables
- Multiple unordered treatments
Cardiac Stents: Statistical Challenges

- Often dozens, hundreds, or even thousands of potential variables
- Multiple unordered treatments
- Multilevel data (e.g., patients clustered in hospitals)
Cardiac Stents: Results

Rose and Normand (2018)
Cardiac Stents: Policy Implications

Implications for patients, hospitals, device manufacturers, and regulators.

- How can this information be incorporated into the patient’s decision-making process?
- Will hospitals reconsider their complex contracting with manufacturers to avoid poorer-performing devices?
- Should manufacturers consider pulling certain stents from the market?
- How should regulators respond to postmarket information that was not available at the time of device approval?
Improving Mental Health Care, 1950-2000

...“substantial progress” made in access to care, financial protection, and meeting basic needs of people with mental illnesses in the U.S. (McGuire 2016)

- Changes in financing & organization of mental health care, not new treatment technologies, made the difference
- “Improvements...evolved through...more money, greater consumer choice, and the increased competition among technologies and providers that these forces unleashed” ⇒⇒⇒
Risk Adjustment in Plan Payment

Over 50 million people in the United States currently enrolled in an insurance program that uses risk adjustment.

- Redistributes funds based on health
- Encourages competition based on efficiency & quality
- Huge financial implications

Ellis, Martins, Rose (2018)
Mental Disorders Top The List Of The Most Costly Conditions In The United States: $201 Billion

Charles Roehrig

ABSTRACT

Estimates of annual health spending for a comprehensive set of medical conditions are presented for the entire US population and with totals benchmarked to the National Health Expenditure Accounts. In 2013 mental disorders topped the list of most costly conditions, with spending at $201 billion.
Mental Disorders Top The List Of The Most Costly Conditions In The United States: $201 Billion

by Kenneth E. Thorpe, Curtis S. Florence, and Peter Joski

ABSTRACT: We calculate the level and growth in health care spending attributable to the fifteen most expensive medical conditions in 1987 and 2000. Growth in spending by medical condition is decomposed into changes attributable to rising cost per treated case, treated prevalence, and population growth. We find that a small number of conditions account for most of the growth in health care spending—the top five medical conditions accounted for 31 percent. For four of the conditions, a rise in treated prevalence, rather than rising treatment costs per case or population growth, accounted for most of the spending growth.
Mental Health and Substance Use Disorders

Profit-Maximizing Insurer:

- Design plan to attract profitable enrollees and deter unprofitable
- Cannot discriminate based on pre-existing conditions
- Raise/lower out of pocket costs of drugs for some conditions
- Distortions make it difficult for unprofitable groups to find acceptable coverage

Demonstrate drug formulary identifies unprofitable enrollees

Rose, Bergquist, Layton (2017)
Mental Health and Substance Use Disorders (MHSUD)

- Risk adjustment recognizes 20% of MHSUD enrollees and compensate plans accordingly

- Individuals with MHSUD can be systematically discriminated against in risk adjustment systems
Privately Insured MHSUD Enrollees

MHSUD sample: 59% female
(Full sample: 49% female)

MHSUD sample average total spending $8K and MHSUD spending $740
Full sample average total spending $4K and MHSUD spending $130

Shrestha et al.(2017)
Privately Insured MHSUD Enrollees

Shrestha et al. (2017)
Global Statistical Fit vs. Group Fairness

**Statistical Learning:** Reduced set of 10 variables 92% as efficient.

Rose (2016)
Global Statistical Fit vs. Group Fairness

Statistical Learning: Reduced set of 10 variables 92% as efficient.

Age 21-34

Inpatient Diagnoses

- Heart Disease
- Cancer
- Diabetes
- Mental Health
- Other

Hierarchical Condition Categories

- Metastatic Cancer
- Hemophilia
- Multiple Sclerosis
- End Stage Renal Disease

with a mental health condition. Web Tables S1–S4 in the online Appendix contain $R^2$ and predictive ratio results for the risk adjustment algorithms that considered a limited subset of variables chosen by the “variable screening” LASSO. These algorithms performed consistently worse across all benchmarks.

Rose (2016); Bergquist, McGuire, Layton, Rose (2018)
Global Statistical Fit vs. Group Fairness

1. baseline formula
   - 13.1%
   - -$2,822

2. + mental health
   - 13.3%
   - -$1,952

3. + substance use
   - 13.3%
   - -$1,731

4a. - liver conditions
   - 13.3%
   - -$1,763

4b. - kidney conditions
   - 10.9%
   - -$1,702

Rose and McGuire (2018)
actions limiting their access to care. Thus, this conventional approach to payment will sustain rather than correct the insurers’ incentive to inefficiently limit access to care for this group.

While this example is extreme, a weaker version of this feedback loop between inefficiencies embedded in the health care system and the incentives embedded in the payments is likely to play out in many more realistic settings.\textsuperscript{1} The general point is that if regulated prices are intended to move the health care system to be more efficient and fair, using existing (inefficient/unfair) patterns of care for purposes of payment calibration is unlikely to be the right approach.
Fairness Definitions and Penalized Regression Methods for Continuous Outcomes in Health Spending

Anna Zink
Harvard University
and
Sherri Rose
Harvard Medical School

In this paper, we synthesize concepts from algorithmic fairness and health economics and then propose new measures and estimation methods to improve risk adjustment formulas for undercompensated groups. We consider risk adjustment formulas unfair if they incentivize differential treatment for undercompensated groups via benefit design. This has been referred to in the fairness literature as disparate impact, which means that, despite the goals of risk
Acknowledgements

Funding:
NIH Director’s New Innovator Award (DP2-MD012722)
NIH R01-GM111339