Computational Health Economics & Outcomes Research

3rd Seattle Symposium on Health Care Data Analytics

October 23, 2018

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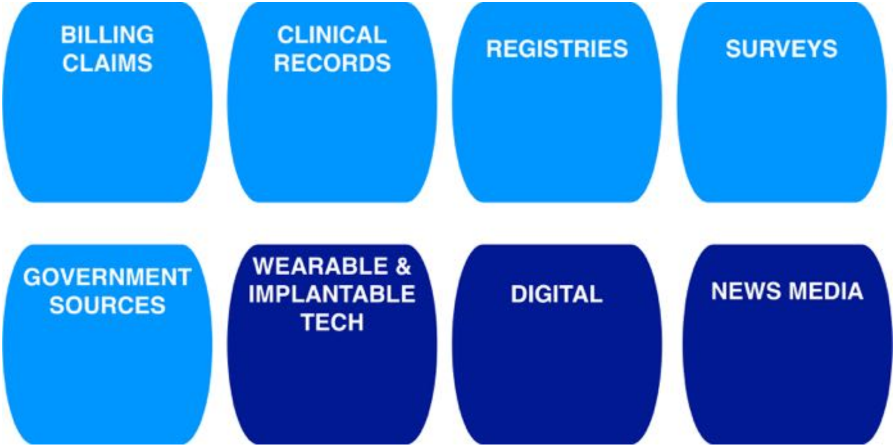
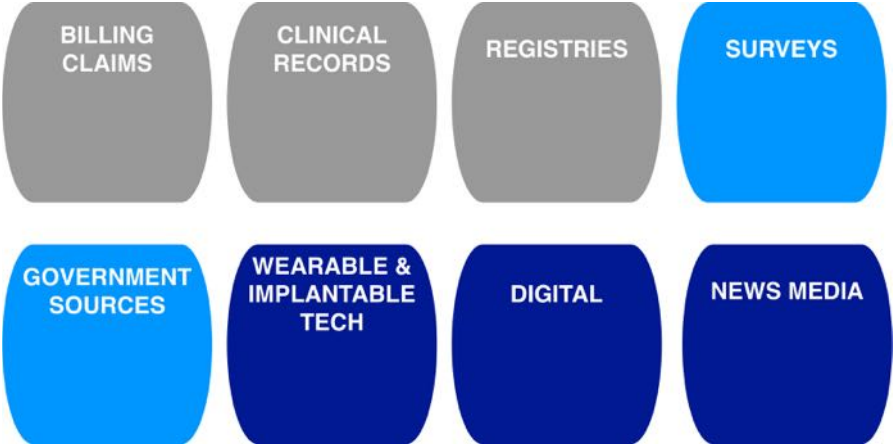

BILLING CLAIMS
CLINICAL RECORDS
REGISTRIES
SURVEYS
GOVERNMENT SOURCES
WEARABLE & IMPLANTABLE TECH
DIGITAL
NEWS MEDIA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BILLING CLAIMS

IBM Watson Health.

CMS

CLINICAL RECORDS

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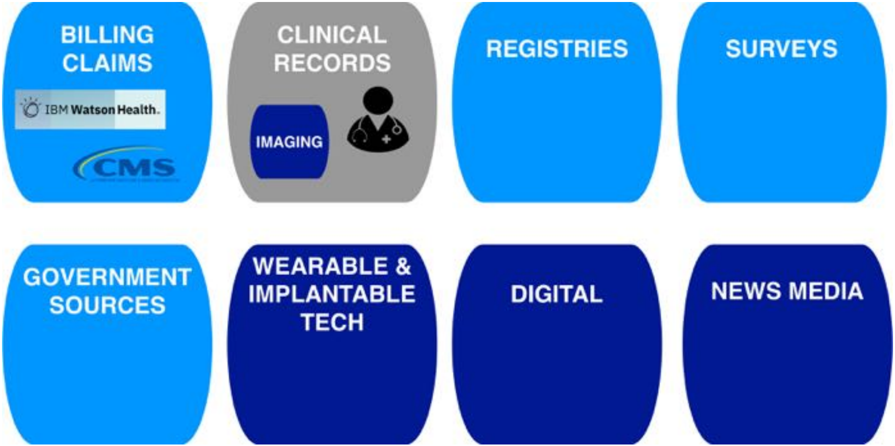
HSR Health Services Research

Robust Machine Learning Variable Importance Analyses of Medical Conditions for Health Care Spending

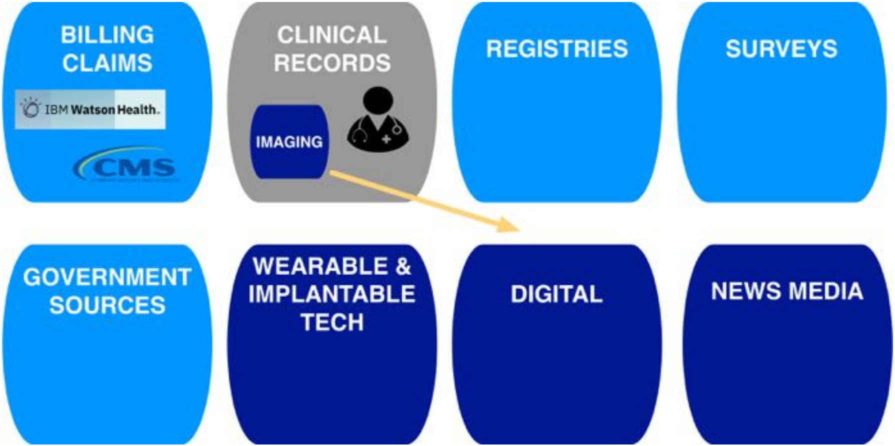
Sherri Rose

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



PNAS

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

Timnit Gebru[a,1], Jonathan Krause[a], Yilun Wang[a], Duyun Chen[a], Jia Deng[b], Erez Lieberman Aiden[c,d,e], and Li Fei-Fei[a]

IBS Biometrics JOURNAL OF THE INTERNATIONAL BIOMETRIC SOCIETY

Double Robust Estimation for Multiple Unordered Treatments and Clustered Observations: Evaluating Drug-Eluting Coronary Artery Stents

Sherri Rose[1,*] and Sharon-Lise Normand[1,2]

Maia Majumder, PhD
Postdoctoral Fellow
Harvard Medical School

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Can Your Hip Replacement Kill You?

By JEANNE LENZER JAN. 13, 2018

SundayReview | OPINION

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TheUpshot

Why Medical Devices Aren't Safer

Austin Frakt
THE NEW HEALTH CARE APRIL 16, 2018

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.

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Your medical implant could kill you

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

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

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MEDICAL TREATMENTS

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

January 17, 2018 · 3:10 PM ET
Heard on Fresh Air

DAVE DAVIES

Queue Download Embed Transcript

FRESH AIR

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)

BROOKINGS

REPORT

Strengthening patient care: Building an effective national medical device surveillance system

Heather Colvin, Pranav Aurora, Saha Khaterzai, Gregory W. Daniel, and Mark B. McClellan ·
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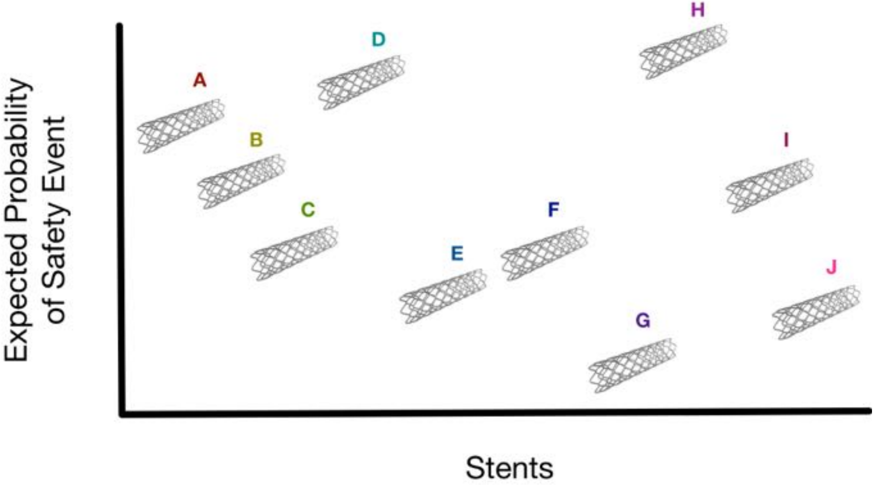
Implantable medical devices represent **high-risk treatments** often evaluated in the premarket setting on the basis of **smaller trials**, are likely to **change quickly over time**, and have led to **serious side effects**.

Cardiac Stents



Stent logo: elmedicointeractivo.com

Cardiac Stents: Statistical Challenges

- Often dozens, hundreds, or even thousands of potential variables

1513	4.163950	3.834244	5.827496
1555	4.277033	3.373982	489.825226
1597	4.390150	3.795142	221.608444
1639	4.503117	3.640379	26.986557
1681	4.616217	3.336954	104.501778
1723	4.729317	3.561723	8.354190
1765	4.842267	3.576960	146.476227
1807	4.955350	3.858309	58.118893
1849	5.068450	3.514176	3.682388
1891	5.181567	3.794615	32.864357
1933	5.294517	3.311670	1.653655
1975	5.407600	3.931615	72.284065
2017	5.520700	4.319901	15.170299
2059	5.633650	3.938955	2.626603
2101	5.746750	3.924497	16.581503
2143	5.859883	3.771340	33.761124
2185	5.972850	3.797512	9.262811
2227	6.085967	3.795501	126.762199
2269	6.199067	3.759673	108.416565
2311	6.312167	3.373145	10.712665
2353	6.425117	3.464702	56.385990
2395	6.538183	3.640879	30.747551
2437	6.651333	3.702649	5.748046
2479	6.764283	3.941036	58.997993
2521	6.877350	3.393778	24.935211
2563	6.990450	3.213435	6.881421
2605	7.103400	3.635089	12.697396
2647	7.216517	3.749416	4.405899
2689	7.329650	3.450428	6.340690
2731	7.442750	3.287580	231.588028

Cardiac Stents: Statistical Challenges

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

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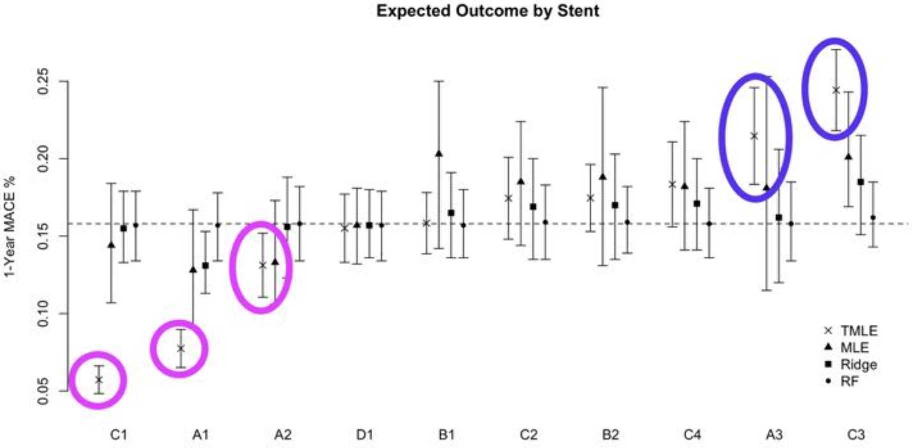
Cardiac Stents: Results



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?

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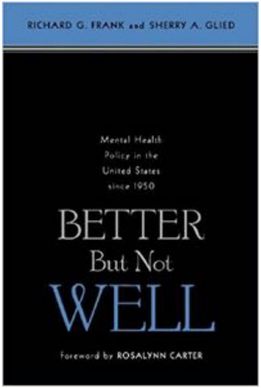
Improving Mental Health Care, 1950-2000

…"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" ⇒⇒⇒

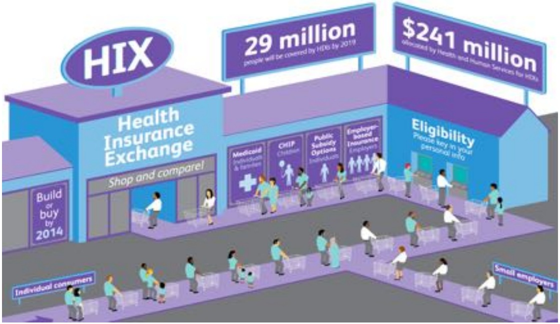


Risk Adjustment in Plan Payment

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

Health Insurance Marketplace



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Ellis, Martins, Rose (2018)

Mental Health and Substance Use Disorders

HealthAffairs

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HEALTH AFFAIRS > VOL. 35, NO. 6: BEHAVIORAL HEALTH

DATAWATCH

Mental Disorders Top The List Of The Most Costly Conditions In The United States: $201 Billion

Charles Roehrig[1]

AFFILIATIONS

PUBLISHED: JUNE 2016 No Access https://doi.org/10.1377/hlthaff.2015.1659

SECTIONS VIEW ARTICLE PERMISSIONS SHARE TOOLS

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 Health and Substance Use Disorders

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Which Medical Conditions Account For The Rise In Health Care Spending?

The fifteen most costly medical conditions accounted for half of the overall growth in health care spending between 1987 and 2000.

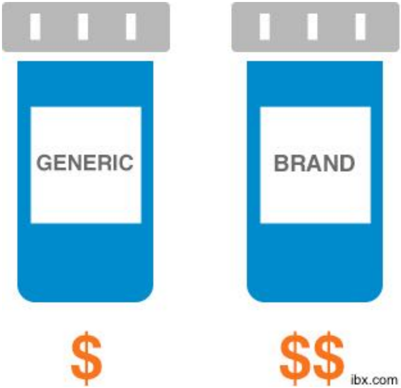
by Kenneth E. Thorpe, Curtis S. Florence, and Peter Joski

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

INSURANCE & PARITY

By Ellen Montz, Tim Layton, Alisa B. Busch, Randall P. Ellis, Sherri Rose, and Thomas G. McGuire

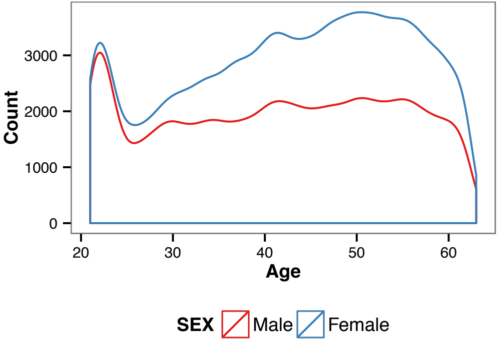
Risk-Adjustment Simulation: Plans May Have Incentives To Distort Mental Health And Substance Use Coverage

- Individuals with MHSUD can be **systematically discriminated** against in risk adjustment systems

Privately Insured MHSUD Enrollees

MHSUD sample: **59% female**

(Full sample: ***49% female****)*

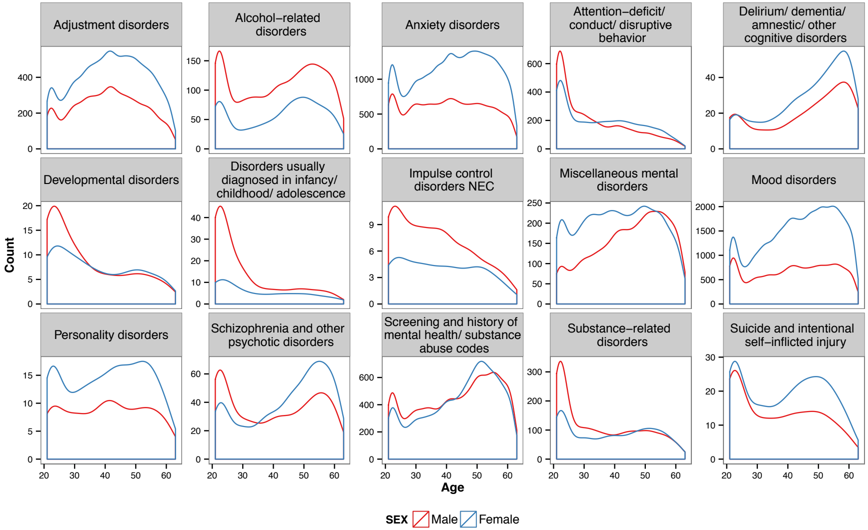


MHSUD sample average total spending **$8K** and MHSUD spending **$740**

Full sample average total spending **$4K** and MHSUD spending **$130**

Shrestha et al.(2017)

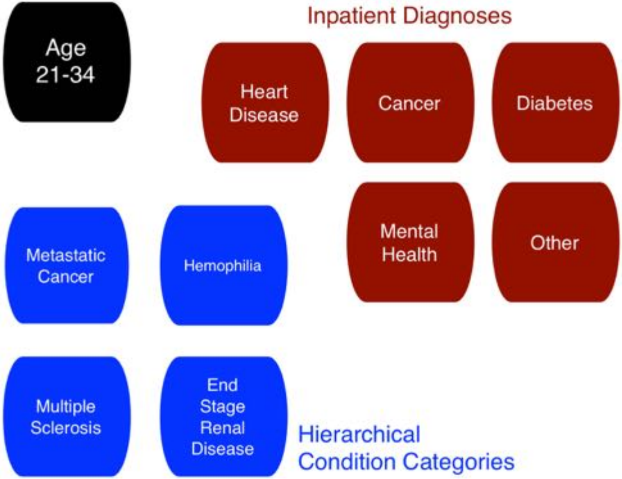
Privately Insured MHSUD Enrollees



Shrestha et al.(2017)

Global Statistical Fit vs. Group Fairness

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



Rose (2016)

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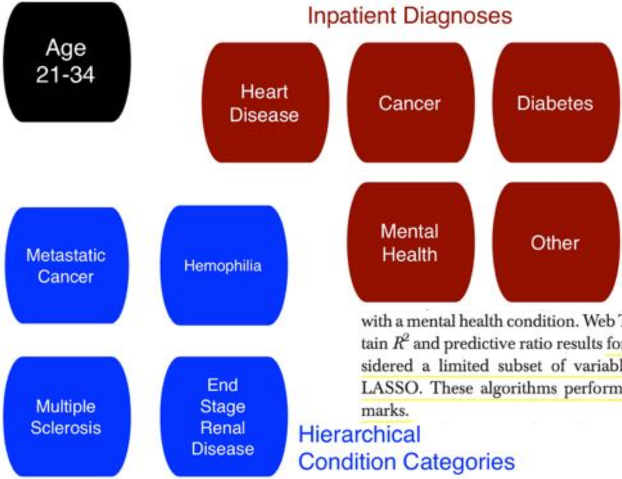
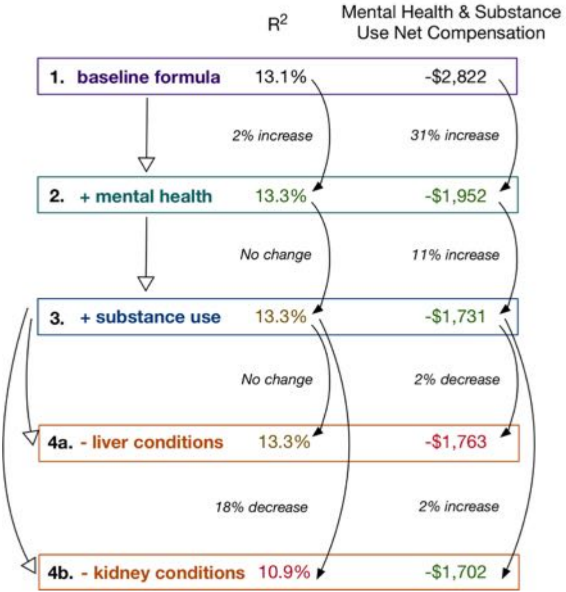


with a mental health condition. Web Tables S1–S4 in the online Appendix contain R^2 and predictive ratio results for the risk adjustment algorithms that considered a limited subset of variables chosen by the "variable screening" LASSO. These algorithms performed consistently worse across all benchmarks.

Rose (2016); Bergquist, McGuire, Layton, Rose (2018)

Global Statistical Fit vs. Group Fairness



Rose and McGuire (2018)

INTERVENING ON THE DATA TO IMPROVE THE PERFORMANCE OF HEALTH PLAN PAYMENT METHODS

Savannah L. Bergquist
Timothy J. Layton
Thomas G. McGuire
Sherri Rose

Working Paper 24491
NATIONAL BUREAU OF ECONOMIC RESEARCH

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.[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.

Savannah Bergquist
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Harvard University

Bergquist, Layton, McGuire, Rose (2018)

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

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Harvard University

Zink and Rose (2018)

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PhD Student in Health Policy

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